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Do ICT development and internet use decrease intra-regional work-related travel?

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ABSTRACT

Technological advancements and the COVID-19 pandemic raised attention about the virtual substitutability of in-person interactions. To learn from the past twenty years' history before COVID, we examine intra-regional work-related trips in the US National Household Travel Surveys. The study finds heterogeneous and dynamic associations between internet usage and work-related travel behavior. First, the overall declining trends are prominent in work-related travel likelihood, particularly between 2009 and 2017, coinciding with the wide acceptance of virtual communication. Second, however, internet usage is often positively associated with the probability of work-related trips in the cross-sectional analysis. For instance, the travel likelihood of internet-savvy sales and service workers was consistently higher than their non-savvy counterparts in the same year. Third, the associations' magnitude and timing are heterogeneous across occupations, possibly because of the differences in the communication types. For example, internet usage positively correlated with sales and service workers' travel likelihood and travel volume per worker throughout the period. In contrast, it was negatively associated with the travel distance of professional and managerial workers in 2001 and their travel volume in 2001 and 2009, suggesting a virtual substitution of costly work-related travel. Although our conclusion is limited to intra-regional travel, the strong declining trend in travel likelihood is a promising element for a sustainable future because travel reduction remains desirable for climate justice, even in the post-pandemic era.

JEL: R4

Keywords: Intra-regional work and business travel, ICT development, (non)internet-savvy, digital and virtual communications

1. INTRODUCTION

One of the most intriguing questions in the age of digital technologies is the extent to which virtual communication can replace face-to-face (FTF) communications. Businesspersons travel for various FTF communications, such as relationship building with clients, business facilitation, and management (Faulconbridge et al., 2009). Over the last 20 years, production networks and product markets have expanded exponentially, thanks to information and communication technologies (ICT). Since businesspersons persistently preferred FTF communications at least before the COVID-19 pandemic (Aguilera, 2008; Lorentzon, 2003; Urry, 2002), business air travel increased as distant communication increased (Beaverstock et al., 2010; Gustafson, 2012; Hislop, 2016). Yet, overall work-related non-commuting business trips (hereafter, work-related trips) didn't increase proportionally with the growth of distant communications (McGuckin and Fucci, 2018). As technology advances, many business units have moved towards "virtual teams" (Townsend et al., 1998) and substituted international and air business travel with virtual ones (Aguilera, 2008; Haynes, 2010). Not many studies analyzed intra-regional work-related travel; however, shorter intra-regional work-related travel behavior may have also changed as ICT adoption modified the business practices (Aguilera, 2008; Haynes, 2010).

Digital transformations of business practices have accelerated since the development and spread of the internet. The global COVID-19 pandemic since 2020 accelerated the trend even further as the pandemic forced enterprises to shift both short- and long-distance travel toward virtual communication. To understand long-run business mobility trends, we believe it essential to understand the inter-relationships between ICT adoptions and work-related trips over the last 20 years. The travel trends in intra-regional trips are particularly important besides international and air travel because intra-regional day trips are frequent and have a large volume in total (McGuckin and Fucci, 2018). In addition, they are significant sources of air pollution, greenhouse gas emissions, and congestion, which should be reduced for a sustainable future (de Nazelle et al., 2010; Roby, 2014).

This paper examines whether internet usage is positively or negatively associated with the likelihood and travel distances of intra-regional work-related non-commuting trips since 2001. We also address inter-occupational variations in the associations because the literature documents heterogeneity in work-related mobility depending on the nature of work activities and occupational category. Understanding occupational variations in the relationships between ICT and work-related mobility is critical in understanding the potential of technology for travel

replacement, the importance of technologies for occupational mobility and attainment, and even inequalities and the digital divide. Thus, our analysis includes internet savviness as a primary variable of interest and its interactions with occupations. The interactions address the inter-occupational variations in travel behavior differences between daily internet users and non-daily users. We contribute to the literature three folds. First, we obtain insights into short-to-mid-distance work-related travel, which is under-investigated compared to long-distance business travel or commuting trips (Aguilera, 2008; Aguiléra and Proulhac, 2015). Particularly in the research that explores the relationship between ICT and travel behavior, local work-related travel attracted little attention. This paper tries to initiate discussions about the possibility of virtual substitution of local work-related trips using available data. Second, we explore the occupational heterogeneity in the associations between ICT usage and work-related travel behavior. Business communication literature documents that the substitutability of FTF communications by ICT depends on the nature of communications required by jobs. Thus, we compare three occupational groups to highlight the variations: sales and service (SS) workers, professional and managerial (PM) workers, and administrative and clerical (AC) workers. Third, we address the changing associations between ICT usage and work-related trips by comparing three different timings of the US National Household Travel Survey (NHTS), 2001, 2009, and 2017. As technology advances and internet usage becomes almost universal, ICT usage and its impacts on work-related trips may shift from simple travel generation or substitution to more complex modifications in operational processes (Haynes, 2010). Using three repeated cross-sectional data of the NHTS, we explore the heterogeneity of associations by the stages of technology adoption.

Our analysis implies that the spread of internet usage coincides with travel reduction trends, while a cross-sectional study often suggests travel generation (or complementary) effects. We also found occupational heterogeneity in the associations with ICT usage. For example, both cross-sectional complementary effects and inter-temporal substitution effects are stronger for SS workers than for other occupations.

Although our analysis is subject to several data limitations, the declining trend in intra-regional work-related travel seems to be a promising element of our current digital transformation attempts to reduce travel. In the long run, ICT usage might modify business practices, lowering the travel demand of particular occupations, at least for local trips. In addition, the national-level initiatives may effectively accelerate the transition by altering the business norms.

The remainder of this paper is organized as follows. Section 2 looks at the relationships between technological developments and work-related business travel behaviors, and the roles of those digital platforms in business communication. The data, variables, and methods are described in section 3. Section 4 discusses empirical models and variables employed in the analysis. Section 5 explains estimation results and post-estimation predictions. Finally, the last section discusses conclusions and limitations.

2. TECHNOLOGICAL DEVELOPMENT AND VIRTUAL INTERACTIONS IN INTRA-REGIONAL WORK-RELATED BUSINESS TRIPS

2.1 Work-related Business Trips in a Context

Businesspersons occasionally travel to irregular places to visit clients, attend meetings, deliver on-site services, and do other miscellaneous errands (Aguilera, 2008; Faulconbridge et al., 2009). Such work-related non-commuting trips have attracted less research attention than commuting, partly because only a limited number of workers make such trips (Aguilera, 2008; Aguiléra and Proulhac, 2015). However, they share an unignorable proportion of travel. For example, Aguilera (2008) reported that non-commuting work-related trips shared 16% of long-distance trips (50 miles or longer) in the US in 2002. In the UK, 10% of domestic travel distances were business travel in 2010 (Roby, 2014)

Most previous research assessed long-distance business travel, such as air or international travel. More specifically, research on work-related travel behavior has focused on whether ICT developments have increased or decreased such business travel (Aguilera, 2008; Beaverstock et al., 2010; Denstadli, 2004; Roy and Filiatrault, 1998). Some researchers discussed ICT's travel-generation effects (or complementary effects) (Haynes, 2010). They argued that ICT promoted business travel because it brought economic globalization and increased the need for long-distance communication (Aguilera, 2008). Since many businesspersons believed that FTF conversations were essential for relationship building and in-depth communication, more long-distance communication resulted in more business travel (Faulconbridge et al., 2009; Urry, 2002). Indeed, Irish software companies in 2005 considered that business travels are essential for building and maintaining relationships (Haynes, 2010). Denstadli et al. (2013) also confirmed a positive association between frequencies of videoconferencing and business air

travel, using the data from 2009 and 2010 in Norway. Moreover, other research reports that business air travel increased (Beaverstock et al., 2010; Gustafson, 2012; Hislop, 2016).

Other researchers documented the substitution effects of ICT on long-distance business travel. In the early 2000s, the burst of the dot-com bubble and the 9/11 World Trade Center incident increased companies' cost and risk awareness, leading to digital substitution for business travel (Haynes, 2010). Indeed, the US Department of Transportation (2006) reported that air and international travel substantially declined after the 9/11 attack and did not return to the pre-incident level for a few years. While there was no significant decline in the "percent" of business air travel in the pre- and post-9/11, the "total amount" of estimated air trips had the largest decline of all modes, with a nearly 22 percent decline in the air trips on an annualized basis (US Department of Transportation, 2006). If we take the estimated reduction in air travel and apply the shares of air business trips, shown in Table B1 of the report, there would have been an estimated 14% decline in air business trips. While short air travel (less than 100 miles) might have been partly replaced by vehicle travel (US Department of Transportation, 2006), virtual communication might have partially substituted business travel after 9/11. For instance, Denstadli (2004) found that videoconferencing replaced 2.5 to 3.5% of domestic business air travel in Norway, using the data collected in 2003. Lu and Peeta (2009) also confirmed the substitution effects on business air travel, using a survey of the Taiwanese technology industry in 2007. Another wave of virtual substitution came around 2008 when the global financial crisis hit the economy, and climate change attracted public attention (Poom et al., 2017; Roby, 2014). And the latest wave came in 2020; the COVID-19 pandemic has forced companies to substitute face-to-face interactions with virtual ones (Hacker et al., 2020).

Despite the sizable literature on long-distance business travel, discussions about local work-related trips are limited. Yet, they are still worth research attention because frequent local work-related trips can be more bothersome in total compared to infrequent international travel (Lo et al., 2013), affecting individual travelers' subjective well-being. Moreover, local short-distance trips are costly for society's environmental health and climate change because they are significant sources of congestion and greenhouse gas emissions (de Nazelle et al., 2010). Although airplanes are known for their environmental pollution, the large volume of travel conducted by car makes the overall impact of car travel more substantial than infrequent travel by plane. For instance, Roby (2014) documents that vehicles take up 56% of carbon emissions from business travel in the UK, and the share of surface transportation land transportation (car,

train, and taxi) is 65% altogether. Contrary, the percentage of airplanes is 24%. Thus, additional research on local work-related trips is necessary.

The US NHTS provides data about local work-related trips other than those of commercial drivers (e.g., taxi drivers). Due to their focus on day trips, more than 70% of the work-related business trips recorded in the three most recent NHTS have a travel distance of fewer than 50 miles, most of which are made by private vehicles (McGuckin and Fucci, 2018).

Between 2001 and 2017, there were signs of changes in short-to-mid-distance work-related travel behavior. NHTS data reports that the average work-related travel mile per person per day in the US declined; from 3.41 in 2001 to 2.28 in 2009 and 1.42 in 2017 (McGuckin and Fucci, 2018). Since the NHTS focuses on day trips, this substantial decline means a decline in intra-regional travel, either in frequency or distance per trip. Furthermore, during the COVID-19 pandemic, videoconferencing systems replaced most FTF interactions, including local ones (Hacker et al., 2020). It is uncertain to what extent online communication will remain a virtue in the post-pandemic era, given the resumption of in-person interaction and office attendance. However, the norm of business practices has undoubtedly changed, which may result in a permanent decrement in business travel.

2.2 ICT Developments, Internet Usage, and Business Communications

The relationships between virtual communications and business travel have changed as technology advances. Figure 1 summarizes three stages of ICT development between 1990 and 2020, following the literature. First, in the early stage of internet diffusion (1995-2001), PCs and mobile phones spread for business communication before household use (OECD, 2012). On average, 80% of large corporates used the internet in 2000, while household use hovered around 40%, even in developed countries (OECD, 2001). Technologically, simple mail transfer protocol (SMTP) and file transfer protocol (FTP) built the basis for virtual collaboration at the workplace and one-to-one digital correspondence with clients (Kettinger and Grover, 1997). The emergence of the internet also accelerated operational integration and inter-organizational partnerships (Shiels et al., 2003). As ICT lowered communication costs, production networks and market areas expanded geographically, increasing the need for distant communications (Aguilera, 2008). However, ICT in that era was far from a substitute for in-person meetings, particularly in building relationships and dealing with complex communications (Chidambaram, 1996; Lorentzon, 2003; Urry, 2002; Walther, 1995; Warkentin et al., 1997).

During the second stage of ICT development (2001-2010), web-based interactions enabled complex production coordination across remote locations. The spread of PCs, developments in cloud computing, transitions from personal digital assistants (PDAs) to smartphones, and evolutions of third-generation wireless technologies (3G) also helped business globalization by increasing the quality and coverage of data exchange (Figure 1). By the end of the second stage, the internet had become an essential tool for business: 95% of companies employed email, 91% used the internet, and 79% owned their website (Barley, 2015; The World Bank, 2016).

The surge of mobile internet also altered trip planning processes and work styles. For example, ICT enabled workers to chain business trips, particularly short ones, reducing the likelihood and distance of travel (Smoreda and Thomas, 2001; Srinivasan and Raghavender, 2006). The prevalence of internet access via smartphones and lightweight laptops also altered business travelers' time use during out-of-office hours (Laurier, 2004). As a result, workers remained productive even when traveling because they could work from anywhere (Roby, 2014), which may increase travel demand.

The latest ICT development stage is from 2010 to the present (Figure 1). Since 2010, the fourth generation long-term evolution (4G) mobile technology, advanced smartphones, and more sophisticated virtual communication tools have pushed the digital shift of businesses even further. Internet usage continued to rise and became an essential infrastructure for businesses and privates. In 2016, over 95% of companies and 85% of individuals had broadband connections (OECD, 2017). About 73% of adults in developed countries used the internet daily in 2016, a dramatic rise from 30% in 2005 (OECD, 2017). For business communications, innovations in virtual collaboration applications such as Zoom, Microsoft Teams, Skype for Business, and Slack have made remote interactions more natural (Baldwin, 2019). Furthermore, advancements in virtual reality and augmented reality dissolve the boundary between real and virtual interactions, reducing the advantages of FTF communications (Seidel et al., 2021).

Besides the advancements in applications, the proliferation of mobile internet tools has blurred the boundaries between internet usage for business and personal lives (Büchler et al., 2020; Wajcman et al., 2008). By 2007, constant connectivity to work via mobile devices was reported to invade two-thirds of workers' personal life through incoming calls and emails during private time (Wajcman et al., 2008). Constant connectivity also reshaped traditional face-to-face interactions even further; it reinforced the meeting requirements for interactions that demand in-depth understandings or serendipities while reducing the meeting need for routine

communications or background tasks (Azad et al., 2016). In addition, constant connectivity via smartphones also relaxed spatiotemporal binds of personal life, altering workers' availability and attitudes towards work-related travel (Hughes and Silver, 2020; Neutens et al., 2011; Schwanen and Kwan, 2008; Wajcman et al., 2008). The adoption of technologies in private life also altered communications with consumers. As online shopping and social media became popular, e-commerce and web-marketing tools gained their importance, shifting weights from outside sales (selling goods or services in-person) to inside sales (selling products or services remotely via phone, internet, or other communication channels) (Thaichon et al., 2018).

2.3 Business Communications and ICT Usage across the Occupations

Analysis of work-related trips demands a nuanced approach because the reasons and characteristics behind work-related trips vary substantially by occupation, industry, and organizational context (Beaverstock et al., 2010; Jones, 2013). As discussed earlier, some work-related trips are for communications easily substituted by ICTs, while others are not.

Table 1 summarizes the literature's findings on communication types and their likelihood of virtual substitution (Arnfalk and Kogg, 2003; Daft and Lengel, 1984; Denstadli, 2004; Denstadli et al., 2012). The table also summarizes the occupational variations in communicative characteristics based on the literature. Tasks that can be efficiently conducted online include internal relations between familiar members, which require learning up to an intermediate level (Arnfalk and Kogg, 2003). Hence, virtual meetings are appropriate for short and repetitive management meetings (Arnfalk and Kogg, 2003; Poom et al., 2017). On the contrary, external relations, such as client visits and customer service, depend more on FTF meetings (Aguilera, 2008, Faulconbridge et al., 2009). Communications for the relationship-building phase are complex and delicate, and ICTs work as complementary tools to accelerate mutual understandings rather than alternative means for visits (Denstadli, 2004). In-person meetings are also preferred for intensive discussions, brainstorming, and creative planning processes (Faulconbridge et al., 2009). Businesspersons also travel long distances for conferences and trade shows to fulfill multiple purposes beyond simple information exchange (Mokhtarian, 2009).

Among various occupations, SS workers are more likely to communicate with external partners, often leading to high dependence on FTF interactions (Ohiomah et al., 2020). In external communications, the cumulative volume of contacts is essential for relationship-building and getting contracts (Ahearne et al., 2007). Thus, in the early 2000s, technologies are typically introduced for targeting potential customers rather than substituting FTF contacts (Ahearne et al., 2007). However, technological developments in sales force automation and customer relations management (CRM) have changed the business practices of SS workers and increased their productivity (Ahearne et al., 2012; Delpechitre et al., 2019; Marshall et al., 2012; Rapp et al., 2008). For example, salespeople can specify prospective customers efficiently by using CRM. As a result, outside salespeople can reduce the time lost in random door-to-door selling. The emergence of e-commerce and social media also increased the weight of inside sales and online marketing (Marshall et al., 2012; Thaichon et al., 2018). As customers rely more on the data available through the internet than personal connections, inside sales increased their importance in successful sales. Indeed, research reports that buyer-seller trust and salespeople's time devotion became significantly less relevant to business-to-business sales after 2010 than pre-2010 (Ohiomah et al., 2020). As a result, corporates now adopt a hybrid sales structure, which combines inside and outside sales with e-commerce channels (Thaichon et al., 2018).

Implications for PM workers are more mixed than for SS workers. On the one hand, the advent of technologies may reduce FTF meetings by realizing virtual teams. As Duarte and Snyder (Duarte and Snyder, 2006) argue, managerial workers in the 21st century actively use virtual communications to develop and accelerate remote collaborations. Companies often virtually substitute costly business travel because videoconferences are effective for regular management meetings (Arnfalk and Kogg, 2003; Denstadli, 2004; Faulconbridge et al., 2009; Lu and Peeta, 2009; Lyons, 2013). On the other hand, research also found that some communications made by PM workers remained persistently in person. PM workers are inherently involved in complex communication for strategic planning, creative design, and multicultural adjustments, which are more efficient in FTF meetings than virtual ones (Faulconbridge et al., 2009; Denstadli, 2004). Thus, the degree of virtual substitution varied substantially across the firms, at least before the COVID-19 pandemic (Richter, 2020).

3. DATA, VARIABLES, AND METHODS

We employ the NHTS of 2001, 2009, and 2017 for the analysis. The NHTS provides a comprehensive picture of daily, repetitive, and intra-regional travel behavior in the US, including work-related non-commuting trips. Our study targets workers of all ages each year. As the NHTS offers sampling probability weights of persons, we apply them (*wtperfin*) for descriptive statistics and regression analyses.

This study broadly defines work-related business trips, namely, all the trips made for work-related business objectives other than commuting (Andersson et al., 2020). They include but are not limited to traveling to an irregular place of work, visiting clients, attending a meeting or conferences, and providing on-site services (Aguilera, 2008). They also include miscellaneous work-related errands, such as picking up or dropping off co-workers or items, going to print shops to make copies or pick up signs, buying office supplies, and getting company vehicles serviced. The definition follows the previous studies and the NHTS. For consistency, we use WHYTRP90 in the NHTS to find work-related business trips (WHYTRP90=02) because more detailed travel purposes (*WHYTO*) have changed their categories between surveys.

We focus on short-to-mid-distance trips. It is primarily because they are much more frequent yet under-investigated trips among work-related travel. Using the NHTS data also forces us to do so because the surveys are designed for day trips. For example, the NHTS data are highly likely to miss the long-distance, less-frequent, and multi-day travel because travel records of the NHTS are one-day snapshots of the travel. In the data collection process, those absent from home the entire day of the survey were exempted from travel diaries. Moreover, those who are regularly away from home are less likely to answer those surveys.

To ensure our focus on the intra-regional trip, we excluded all the travelers who made air travel or a trip longer than 200 miles one way. We apply these standards to remove inter-regional and overnight travel because it may have different characteristics from regular local day trips. For example, a trip of 200 miles corresponds to roughly the 95 percentile of the work-related travel mile, and it is less likely to be a day trip for car travel, considering the travel time.

We assess whether internet usage is positively or negatively associated with work-related travel likelihood and daily travel distance. Internet usage is indicated by an internet-savvy binary variable (*savvy*), which is one if the person has used the internet daily for the past six months

and zero otherwise. Due to the data limitations, the purpose and location of usage are not considered. Ideally, we should measure the intensity of internet use specifically at work; however, such data are unavailable for 2009 and 2017. Thus, we employ the internet-savvy variable explained above for consistency.

We also test alternative variables for internet savviness: internet use frequencies in an ordinal variable (*webuse*) for all years and an indicator variable of web use at work (*webwork*) in 2001. In addition, we examine daily internet access via smartphone (*sphone*) and multiple devices (*multi*) for 2017.

The *webuse* measures internet frequency using a zero to four scale (0: never, 1: a few times a year, 2: a few times a month, 3: a few times a week, and 4: daily). Therefore, if the *webuse* equals four, the *savvy* is one, and if the *webuse* is zero to three, the *savvy* is zero. The *webwork* variable indicates whether the worker uses the internet from the workplace without indicating the frequency. In 2001, 51.7% of workers and 59.3% of work-related trip makers used the internet at work, slightly higher than the share of internet savvy (Table 2). The correlation between *savvy* and *webwork* is 0.442. The high correlations between *savvy* and *webwork* show that the internet-savvy indicator reasonably represents internet familiarity for work purposes, although it is not perfect. For 2017 data, *sphone* indicates whether the person used the internet daily via smartphone (1 if the person uses the internet daily via smartphone, and 0 otherwise). Another variable, *multi* is also generated to measure those who used multiple types of devices daily for internet access. Previous research says that although smartphones are used for a wide range of tasks, PCs (either desktop or laptop) are often preferred for handling complex tasks (Bröhl et al. 2018). Thus, we employ *multi* to exclude very light internet users, who only access the internet for short messaging, SNS, or online shopping. Smartphone users constituted 87.0% of workers and 88.6% of work-related trip-makers (Table 2). Daily users of multiple devices are 77.3% of workers and 81.0% of work-related trip makers; many businesspersons use both mobile devices and PCs daily.

Among four occupational categories included in the data, we assess the travel behavior of workers in three occupations: SS, PM, and AC workers. We exclude workers in the manufacturing, maintenance, and farming category because ICT hardly substitutes their tasks.

Daily internet users continually increased from 2001 to 2017 (Table 1); the proportion of internet-savvy workers was 47.5% in 2001, 74.5% in 2009, and 96.7% in 2017. The internet-

savvy workers' share among work-related trip makers is even higher than among all workers: 53.6% in 2001, 79.3% in 2009, and 98.2% in 2017. Work-related trip makers are slightly senior, more likely to be non-Hispanic White males, and have a higher household income than the worker average.

From 2009 to 2017, the number of work-related trip-makers declined while the number of workers increased (Table 2). This rapid decline in the latter half of the observation period is consistent with business practices literature. That is, there was a pivotal shift in balance from outside to inside sales and remarkable advancements in data-sharing and virtual communication tools.

Business travelers' demographics shifted slightly to improve the balance between genders and racial/ethnic groups (Table 2). Yet, business travel remained dominated by non-Hispanic White male workers. The average age of work-related trip makers also remained higher than the workers' average.

Daily travel miles of work-related trips also decreased from 2001 to 2017. For instance, the number of people who made work-related non-commuting trips has reduced from around 8.5 million in 2001 and 2009 to 4.7 million in 2017 (Figure 2). In addition, the share of shorter trips has increased. The proportion of work-related trip makers who traveled less than 5 miles per day increased from 20.6% in 2001 to 32.8% in 2017, while the share making longer business trips (50 miles or more) decreased from 24.4% in 2001 to 15.0% in 2017.

Table 3 compares internet-savvy and non-internet-savvy workers in 2001, 2009, and 2017. Throughout the period, internet-savvy work-related trip makers were younger and more likely to live in urbanized areas than their non-savvy counterparts. Notably, the gap in the average age between internet-savvy and non-savvy workers widened from 1.9 years in 2001 to 8.9 years in 2017. The diffusion speed of technology also varied by occupation. The internet-savvy share was higher among PM workers than in other occupations. In 2001, 57.0% of PM workers were internet savvy, while the percentages were 34.7% and 45.9% for SS and AC workers. By 2017, the difference between occupations became minor as almost everyone became internet-savvy. The *webwork* for 2001, as well as *sphone* and *multi* in 2017, show a similar tendency. Namely, those who used the internet at work in 2001 were more likely to be young, male, with a college degree, in urban areas. PM workers always show the highest percentage of internet savviness, even with alternative measures.

4. THE MODEL

We employ the Heckman selection model, which simultaneously estimates the daily travel distance of work-related trips and a selection model for the probability of making any work-related trips (Heckman, 1976). Heckman's model is often utilized when selection bias exists. In our case, workers who made work-related trips (selected) may differ from those who did not make any work-related trips (not selected). Heckman's model estimates the selection process using the Probit model. The daily travel distance of work-related trips is calculated for those who made business trips.

Assume that the primary regression of interest is;

$$y_{it} = X_{it}\beta + \varepsilon_{it} \quad (1)$$

, where y_{it} is the natural log of daily work-related travel distance (in miles), and X_{it} is a set of observable characteristics of worker i in year t. β is a vector of coefficients, and ε_{it} is a normally-distributed error term. Due to the selection bias, we observe travel miles only for workers who made work-related trips, where an indicator function z_{it} is equal to one;

$$z_{it} = \begin{cases} 1, & W_{it}\gamma + \mu_{it} > 0 \\ 0, & W_{it}\gamma + \mu_{it} \leq 0 \end{cases} \quad (2)$$

W_{it} is a set of independent variables in the selection process of worker i in year t, which may contain overlapping variables with the explanatory variables employed in the distance analysis (X_{it}). γ is a vector of coefficients, and μ_{it} is a normally-distributed error term.

Two error terms are distributed as follows;

$$\varepsilon_{it} \sim N(0, \sigma^2)$$

$$\mu_{it} \sim N(0,1)$$

$$corr(\varepsilon_{it}, \mu_{it}) = \rho \quad (3)$$

where ρ and $\lambda = \sigma\rho$ are to be estimated. When the correlation between errors (ρ) is not zero, Heckman's selection model provides unbiased and consistent estimations of the parameters.

The explanatory variables in equations (1) and (2) (i.e., X_{it} and W_{it}) consist of an internet-savvy indicator variable, categorical occupation variables, personal characteristics, location characteristics, and their interactions. The primary independent variable, internet-savvy ($savvy_{it}$), is equal to 1 if internet usage is "daily" and 0 otherwise. Categorical variables for occupations distinguish SS and PM workers from AC workers. As personal characteristics, we employ age, gender, racial-ethnic groups, household family income, and educational attainment. Age is included as a continuous variable. Racial-ethnic group indicator variables address differences among non-Hispanic whites, Afro-Americans, Asians, Hispanics, and others. As the household family income, we use the median value of each income category range (in logarithm). Educational attainment is addressed by whether the person has a college degree. Locational heterogeneity is controlled by four Census workplace regions (Northeast, Midwest, South, and West) and whether the worker lives in an urbanized area (*urban*=1 if the worker lives in an urbanized area, and 0 otherwise). Last, we distinguish between weekdays and weekends and among the observation years by employing indicator variables.

Heckman's selection model is sensitive to collinearity between X and W, and the variance of λ (Winship and Mare, 1992). If the multicollinearity is severe, conducting the selection probability analysis and the subsample analysis of the outcomes separately (i.e., two-step model) is more robust (Puhani, 2000). Since we do not have much variation in the explanatory variables, the risk of multicollinearity between X and W is high. Thus, we compare the results from the Heckman models with those obtained using two-step models.

We also test the findings' robustness by employing alternative internet-savviness measures as explained in Section 3: the internet usage frequency as the ordinal variable (*webuse*) for all years, internet usage at work (*webwork*) for 2001, internet usage by smartphone or multiple devices (*sphone* and *multi*) for 2017.

We use the model structure to examine inter-occupational differences for each year. The model includes interactions between internet use and occupation. Then, we calculate the marginal effects of the main variables with interactions and conditional predictive margins for facilitating interpretation. The average marginal effects are calculated as follows; the marginal increase/decrease associated with the factor change (e.g., from $savvy_{it}$ =0 to $savvy_{it}$ =1) is calculated for each observation in the data and then averaged. Because the model contains interactions, we calculated the average marginal effects by occupational group. In other words, the average marginal effect of $savvy_{it}$ is predicted for SS, PM, and AC workers. We also

conducted an occupation-specific pooled analysis of three time periods to confirm the inter-temporal trends. The results are summarized in the appendix for those who are interested.

Conditional predictive margins show the predicted likelihood of making work-related trips and predicted travel distances if traveled for a worker with specific characteristics. In our case, we employ stereotypical work-related trip-maker characteristics to control factors other than variables of interest (internet-savvy, occupation, and year). Detailed features are explained in Section 5.2.

5. RESULTS

Tables 4 and 5 summarize the results for each year using $savvy_{it}$ as the primary explanatory variable. Table 4 shows coefficients from the analysis. The top part (columns with the suffix -D) offers the results of distance analysis (y: natural log of travel miles), and the bottom part (columns with the suffix -P) shows the results of the travel probability (z: whether the person made any work-related trips). For each year, we offer results from two-step models in the left columns (columns 1, 3, and 5). The results from the Heckman models are summarized in the right columns (2, 4, and 6). For each stage of each model, Pearson correlation coefficients between predicted and observed values are calculated to indicate the model fitness in the selection and distance analyses. Table 5 summarizes the marginal effects of being internet-savvy by occupation for a more straightforward interpretation of the findings. In each year, Heckman's model results are similar to two-step models, although ρs are significantly different from zero in 2001 and 2017, suggesting that selection bias is evident.

Table 6 displays the estimated marginal effects of alternative internet-savviness measures. The first three sets of columns show the results of *webuse* (Table 6, Models R1 to R6). Namely, how much marginal change in distance/probability is associated with one categorical shift in the internet usage frequency. The set of columns R7 and R8 summarize the outcomes of *webwork* for 2001. Columns R9 to R12 summarize the results for *sphone* and *multi* for 2017. In each set of columns, the left shows the average marginal effect estimated from the two-step models, and the right shows those from the Heckman selection models.

5.1 Differences in the Work-related Travel Behaviors between Internet Savvy and Non-Savvy Workers

Differences in the selection process

The associations between internet usage and work-related travel vary by occupation and year. For instance, internet-savvy SS workers were consistently more likely to travel than their non-savvy counterparts in 2001 and 2009, suggesting complementary effects on net (Table 5 Models 1-P to 4-P). In 2017, the coefficient became insignificant due to the large standard error caused by the universal spread of internet usage (Table 5 Model 5-P and 6-P). The coefficient in 2017 is also insignificant in the analysis with alternative measures (Models R9-P to R12-P). Yet, the coefficient remained positive in all models tested in Tables 4 to 6. In addition, it is significant when considering variations among the non-savvy workers (Model R5-P and R6-P in Table 6). As the literature suggests, the counteracting substitution effects were weaker for SS workers than for other occupations because SS workers traveled mainly for external communications or on-site services that were less substitutable by virtual ones. Instead, internet usage provided advantages to internet-savvy SS workers over non-savvy ones by effectively targeting and reaching potential customers.

For PM workers, being internet savvy did not significantly correlate with the likelihood of making work-related trips (Tables 5 and 6). However, the magnitude of the association steadily grew from 2001 to 2017 and turned positive in 2009 and 2017 (Table 5). The standard error in 2017 is much greater than in earlier years because almost all the PM workers used the internet in 2017, which kept the coefficient insignificant despite the greater magnitude than in earlier years. When the variations within the non-savvy workers or the differences in access devices are considered for 2017, PM workers who use the internet more often (those with greater *webuse*) or use smartphone daily (*sphone*=1) are significantly more likely to travel than non-users (Table 6, R5-P, R6-P, R9-P, and R10-P). Frequent internet connections via mobile devices might have become essential for PM workers who need to travel often.

Last, the results were also unclear for AC workers; the coefficients are mostly insignificant, and the signs of the association were unstable (Tables 5 and 6).

Findings for other variables are consistent with the literature. For instance, females were significantly less likely to travel than their male counterparts, as Aguiléra and Proulhac

(Aguiléra and Proulhac, 2015) discussed. The gender gap in the travel likelihood narrowed and became insignificant by 2017 (Table 4). Senior workers and those with higher household family incomes were more likely to travel (Table 4), agreeing with previous findings (Aguiléra and Proulhac, 2015). Besides age and gender, the racial-ethnic group and education affect the chance of work-related trips; non-Hispanic Whites males with college degrees traveled the most, even after controlling for age, occupation, and household income. The finding implies a positive relationship between the hierarchical position and business travel, as the literature reports (Arnfalk and Kogg, 2003; Limtanakool et al., 2006). Last, people traveled more for work-related business purposes on weekdays than weekends.

Differences in the travel miles

The associations between internet savviness and travel miles were less evident than those in the selection model, with a stronger probability of suggesting negative associations. For instance, the association between internet savviness and travel distance was likely negative among SS workers in 2001 and 2017, based on the Heckman selection models (Models 2-D and 6-D). The coefficient is insignificant in the two-step analysis (Table 5 1-D, 3-D, and 5-D); however, all the coefficients are negative.

The travel miles of internet-savvy PM workers were significantly shorter than non-savvy PM workers in only 2009 (Table 4 Models 3-D and 4-D). As the literature documents, the finding implies that PM workers might have selectively reduced longer-distance travel, even for day trips (Roby, 2014). For other years, the travel miles were not significantly different between internet-savvy and non-savvy workers. The coefficients are positive and significant in alternative models of Models R5-D and R9-D (Table 6). Last, the associations between internet-savvy and travel distance for the AC workers were mixed for all years (Table 5).

The associations with other variables are also less evident than those in the likelihood of engaging in work-related trips. For example, the signs of age coefficients are unstable. College-graduate workers traveled fewer, not greater, miles than those without college degrees. And lastly, locational variations disappeared in more recent years. Nonetheless, similar to our findings for the selection stage of the models, men traveled more miles than women, and workers with higher household family incomes traveled more miles than those with lower household family incomes (Table 4). Last, the gender gap in travel distance narrowed but persisted in 2017 (Table 4).

5.2 Conditional Prediction of Likelihood and Travel Distances

We predict the conditional probability of making trips and the daily travel miles of work-related trip makers based on Heckman selection models to facilitate further discussions (Figure 3). We employed the following characteristics in the prediction: a 52 years old non-Hispanic white man with a bachelor's degree living in the Northeast region of the US. As typical work-related trip makers are in the high-income bracket, household income is assumed to be $80,000. We also made predictions using alternative models (two-step models, the Heckman model with an alternative measure for 2017, and the Heckman model with household income increase over the years). However, the outcomes are not significantly different across the four variations; thus, we do not present them here. Please refer to the appendix if you are interested.

Figure 3 shows the conditional probability of making work-related trips (Figure 3, the top part) and the conditional predicted margins of travel distance if traveled (the bottom of the figure). The left column shows the predictions with 95% confidence intervals calculated by the delta-method for 2001 (based on Model 2), the middle column shows those for 2009 (Model 4), and the right column shows the results of 2017 (Model 6). Solid lines and light grey dotted lines represent the results for internet-savvy and non-savvy workers, respectively.

Among the hypothetical internet-savvy workers with stereotypical personal characteristics, the SS worker had the highest probability of making work-related trips and traveled the longest distances in all years (Figure 3). For instance, the travel likelihood was 22% for the internet-savvy SS worker in 2001, with approximately 15 miles of travel per day (Figure 3, left column). The internet-savvy PM worker traveled a little less than his SS counterpart, 18% and 11 miles in 2001. The internet-savvy AC worker traveled the least in 2001: 12% and 7 miles, respectively.

To address the savvy-non-savvy difference in the travel volume per worker (not per traveler), we compared the following figures, the predicted travel distance multiplied by the estimated travel probability. The calculation shows that internet-savvy SS workers traveled 14% more in travel volume than their non-savvy counterparts in 2001, while internet-savvy PM workers traveled 17% less than their non-savvy counterparts in 2001. This finding is consistent with what the literature discussed; complementary effects are more evident for SS workers, while substitution effects are more robust for PM workers.

The inter-occupational gaps in the travel probability and distance among those internet-savvy white male workers narrowed between 2001 and 2017. The gap narrowed primarily because the hypothetical internet-savvy SS worker reduced his chance and length significantly more than his PM and AC counterparts did. The estimated likelihood and travel distance of internet-savvy workers of all occupations in 2009 were similar to those in 2001. In 2017, the travel probability declined particularly significantly for the internet-savvy SS worker. The predicted likelihood for the internet-savvy SS worker became less than 10% in 2017, a more than 50% drop from 2001. Internet-savvy PM and AC workers also lowered their chances of making work-related trips, albeit more modestly. In 2017, the internet-savvy PM and AC workers' travel probabilities fell to 9% and 7%, respectively. The travel distance of the internet-savvy SS worker was also reduced to 12 miles, becoming closer to those of PM and AC counterparts.

The predicted probability for the non-savvy workers with assumed characteristics also lowered during the same period. For instance, the travel likelihood of non-savvy SS workers was 16% in 2001, but in 2017, it became only 5% (Figure 3). Non-savvy PM workers also lowered their likelihood substantially; it decreased from 19% in 2001 to 6% in 2017. Interestingly, the estimated distance traveled by the stereotypical non-savvy worker was longer than that of the internet-savvy workers in the same year, except for AC workers in 2009 and PM workers in 2017 (Figure 3). The travel mile difference was particularly notable for PM workers in 2009; the estimated travel distance was 17 miles for the non-savvy PM worker, 60% longer than that of the internet-savvy SS worker.

In 2009, the travel volume per worker of internet-savvy workers remained higher for SS workers and lower for PM workers than for their non-savvy counterparts. Based on the prediction, internet-savvy SS workers traveled 9% more in travel volume per worker than their non-savvy counterparts, while internet-savvy PM workers traveled 33% less than their non-savvy counterparts. In 2017, the travel volume per worker of internet-savvy SS workers was predicted to be 6% higher than their non-savvy workers, consistent with previous years. Internet-savvy PM workers were expected to be 84% higher than their non-savvy counterparts, reflecting lower travel probability and distance.

In sum, conditional predictions confirm that the magnitude of the probability decline was substantial. The trend is robust for SS workers, reducing the travel chance to almost one-third for the stereotypical SS workers. Travel likelihood also decreased substantially for the PM workers with the same personal and locational characteristics; it became half between 2001 and

2017. The substantial decline among SS workers narrowed the inter-occupational gaps in the travel likelihood. The predictions also confirm that the gap between savvy and non-savvy workers is visible for SS workers but not for PM workers. Non-savvy SS workers were 20% less likely to travel than their internet-savvy counterparts in 2001 and 40% less in 2017.

The travel volume per worker also declined substantially between 2001 and 2017 due to the significant decline in the travel likelihood. In 2009, the predicted travel volume per worker was almost the same as in 2001 for internet-savvy workers, while it slightly increased for non-savvy workers (0.4% and 8% less for internet-savvy SS and PM workers, and 4% and 15% more for non-savvy SS and PM non-savvy workers). However, in 2017, the figures for internet-savvy SS and PM workers were 70% and 60% less than in 2001, and those for non-savvy SS and PM workers were 67% and 82% less than in 2001.

6. DISCUSSIONS

This paper contributes to the literature by shedding light on differences in intra-regional work-related travel behavior between internet-savvy and non-savvy workers, by occupation, and by year. Our study provides three implications. First, there has been a substantial decline in work-related travel needs since 2001, coinciding with the adoption of the internet and various virtual communication technologies. The drop is particularly evident for internet-savvy and non-savvy SS workers, which narrowed the inter-occupational gap in the travel likelihood. While the drop between 2001 and 2009 might have been affected by the vehicle substitution of air travel in the near-term aftermath of 9/11 (comprising more than half of the 2001 NHTS data collection period, which extended from March 2001 to May 2002), the decline appears to be greater than the possible event's impacts because our analysis assessed intra-regional travel shorter than 200 miles.

Second, frequent internet users sometimes travel more than infrequent internet users in the same year, suggesting ICT's complementary effects. For example, internet-savvy SS workers have enjoyed more travel opportunities than non-savvy SS workers since 2001. The gap persisted in 2009 and 2017, when almost everybody became internet-savvy.

Third, the degrees of substitutability and complementarity vary by occupation. For instance, internet savviness had significant associations with the travel behaviors of SS workers. Namely, internet usage was consistently associated with a higher probability, shorter travel distance, and travel volume per worker of SS workers' work-related trips since 2001, although the travel likelihood decreased over the years. The result implies that the internet usage of SS workers had complementary effects, while the societal spread of virtual communication had substitution effects. Such mixed effects are observed, possibly because the digital substitutability of external communications heavily depends on the technology adoption of partners. Contrary, for PM workers, internet savviness did not show significant associations with travel likelihood and travel distance, except for negative associations for travel distance in 2009 and the predicted travel volume per worker in 2001 and 2009. As the literature documents, the counteracting complementary and substitution effects may have made the net effect less visible for PM workers.

This research has several limitations due to the data availability. First, the models cannot address causal impact because NHTS data are repeated cross-sectional data with limited personal information. For example, the data do not address internet usage's purpose and sophistication level. Although our internet-savvy indicator had high correlations with internet usage at work in 2001, its validity for later years is unknown. By 2017, internet usage had become universal, and it became hard to draw boundaries between private and business use. Neither device nor application can define technology usage purely for business as people use various communication tools and online transactions seamlessly in their life. Another missing data in the NHTS is details about travel purposes and occupational characteristics. Thus, we cannot address which type of visit ICT usage had a positive or negative association. The substitution and complementary effects would be more visible if we could control these differences. Furthermore, the eight-year gaps between the observations make it difficult to distinguish permanent and temporary changes between the observation years.

Second, our focus on intra-regional travel limits the ability to capture overall business travel trends. The NHTS data are likely to miss long-distance overnight trips, and we excluded air and long-distance travelers; thus, we cannot extend our conclusion to less frequent inter-regional business travel. Although we find a robust declining trend in work-related travel likelihood, other research finds that business air travel increased during the same period (Beaverstock et al., 2010; Gustafson, 2012; Hislop, 2016). These seemingly contradicting trends may be caused by

heterogeneity in the substitution effects. Namely, the substitution effects on routine interactions with internal members (which are likely intra-regional) are more substantial than on less-frequent interactions with external or unfamiliar partners (which may include most inter-regional and international travels). Unfortunately, our data do not allow us to examine heterogeneity by travel distance.

Lastly, the inter-temporal comparison of the travel survey data can be biased due to the declining response rate. The decline in response is a well-documented phenomenon affecting the quantity and quality of the results across time. Indeed, the survey response rate of NHTS has declined from 41.0% in 2001 to 19.8% in 2009 and 15.6% in 2017 (Federal Highway Administration, 2018). Although weights recorded in the survey data control socioeconomic and geographic unbalances of the data, we cannot tell whether the declines in survey response rates vary by job characteristics. Regarding work-related business travel, the magnitude of the declining response rate may be greater for travel-intensive workers. Thus, the survey cohort might be overrepresented by certain groups of workers who made less intra-regional travel.

Nonetheless, digital transformations of businesses have taken place over 20 years, altering work-related travel needs dramatically. From our analysis, the long-run net effect of ICT on travel demand seems to be negative for daily intra-regional trips. As travel reduction is desirable for climate justice and to prepare for another global pandemic, corporate-level and nationwide strategic investments are awaited for the digital substitution of business mobility. The continuous declining trend in intra-regional work-related travel over the last two decades seems to be a promising element for further reductions. Even though we could not account for other possible factors that impact travel reduction, such as 9/11, our analysis suggests that the mix of substitution, complementary, and modification effects is heterogeneous by occupation. In addition, communication characteristics are critically important to understanding and overcoming the remaining hurdles for further reductions. Future research is anticipated to explore the inter-relationships among business communications, ICT advancements, and travel behavior.

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FIGURES

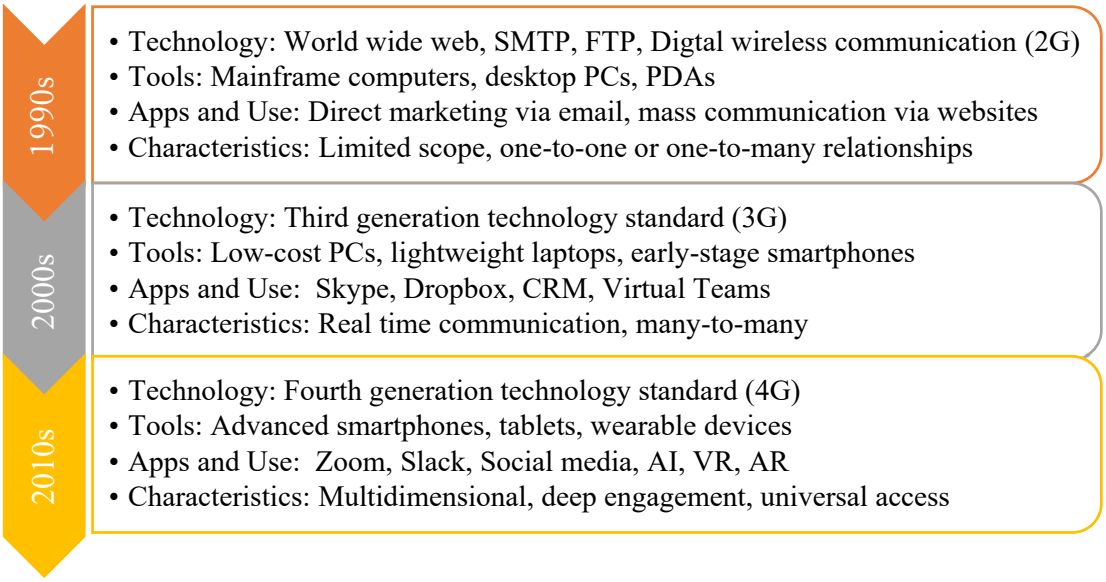


Figure 1. ICT development stages and business communication tools.

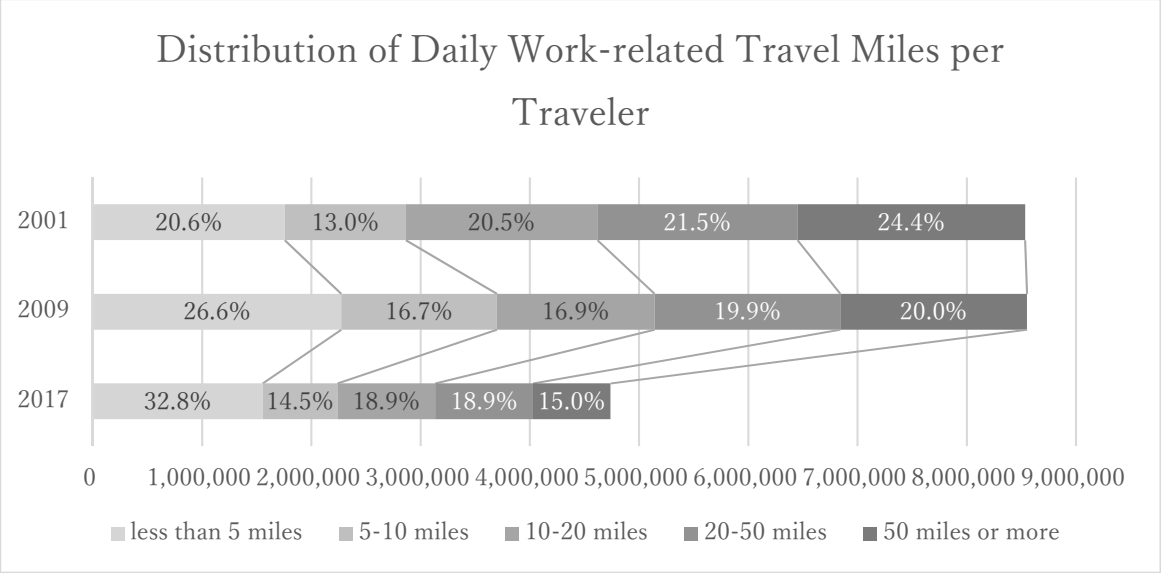


Figure 2. Distribution of daily work-related travel miles per traveler.

Person weights are applied to calculate the population size of each category.
The population size of workers who made work-related trips: 8,534,593 in 2001, 8,550,773 in 2009, and 4,737,776 in 2017.
Source: NHTS (2001, 2009, and 2017).

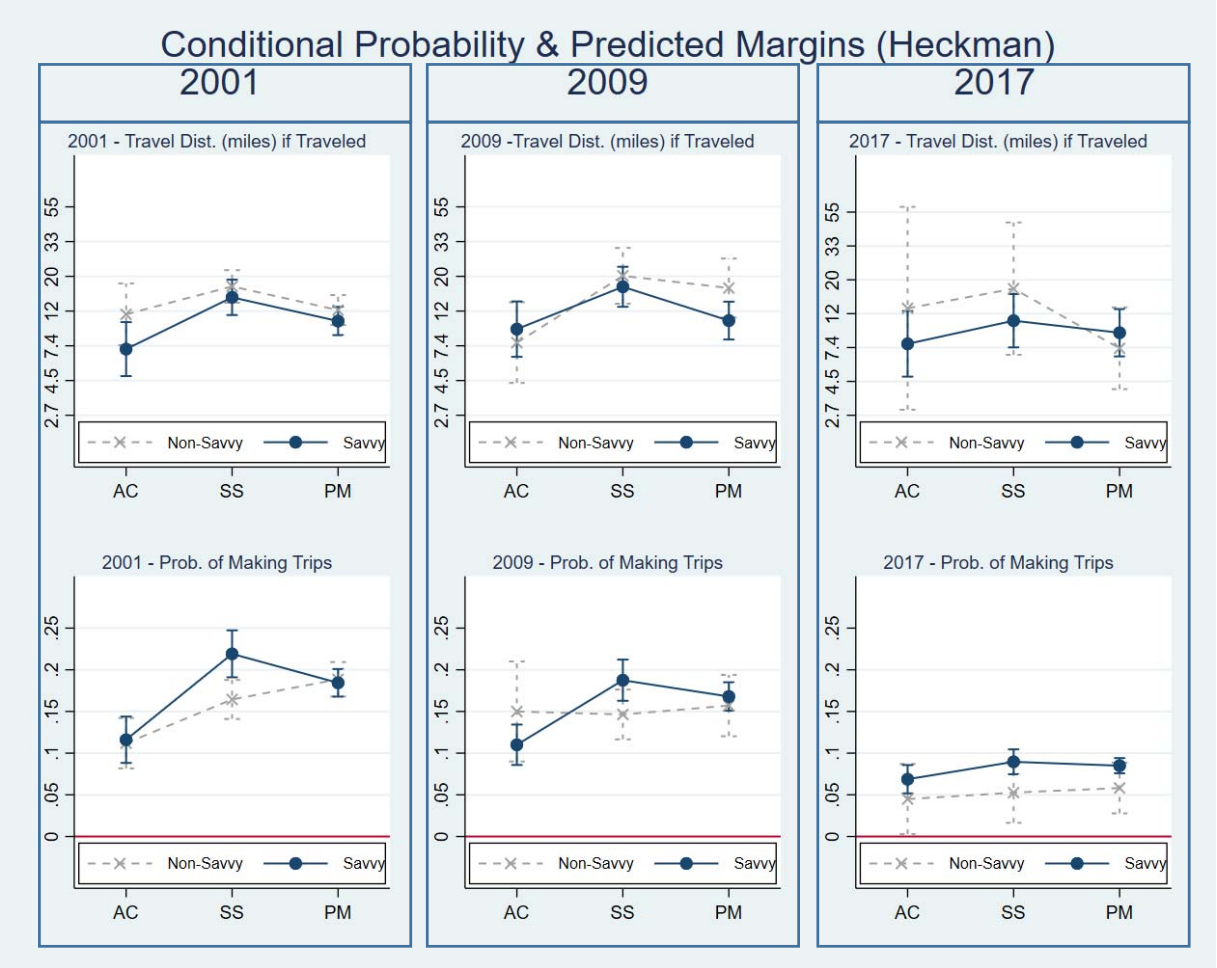


Figure 3. Conditional Probability of Making Work-Related Trips and Conditional Predicted Margins of Travel Distance if Traveled in 2001, 2009, and 2017.

Note: Conditional probabilities are predicted for internet-savvy and non-savvy workers of various occupations with the following characteristics: 52-year-old non-Hispanic white males with a bachelor's degree living in the Northeast region of the U.S., whose household income is $80,000. We used the results of Models A2, A4, and A6 for each year.

TABLES

Table 1. Technology vs. in-person interactions for types of business operations.

	Tasks with a higher probability of virtual substitution	Tasks with higher dependence on FTF meetings
Characteristics of the Tasks		
Members	Internal relations Familiar members	External relations Clients
Communication stages	Informational meetings Recurring regular meetings	Relation building, kick-off
Meeting purposes	Follow-up, check-up Decision-making	Discussion Brainstorming Requires creativity
Duration	Short	Long
Importance	Low	High
Requirements of Media Richness	Low	High
Examples of occupational tasks that may demand travels		
Sales & Serv.	Initial contacts / marketing Regular follow-up	Relationship development with identified clients Service delivery
Prof. & Mang.	Routine reporting/check-up Regular procurement	Strategy developments Initiation of projects/relations (External) collaborations Conferences

Source: Authors' figure is based on literature built upon media richness theory (Arnfalk and Kogg, 2003; Denstadli, 2004; Denstadli et al., 2012; Lengel and Daft, 1984; Walther, 1995), and Deloitte survey 2021 for domestic travel analysis (Caputo et al., 2021)

Table 2. Descriptive statistics on the characteristics of workers and work-related trip makers.

	Workers			Work-related trip makers		
	2001	2009	2017	2001	2009	2017
Observations	53,747	87,198	83,286	5,012	8,543	4,629
Est. Population	91,523,344	96,108,980	101,378,322	8,722,888	8,701,816	4,743,506
% Internet-Savvy	47.5%	74.5%	96.7%	53.6%	79.3%	98.2%
Int. Use Freq. 0-4 Scale:						
4: Daily	47.5%	74.5%	96.7%	53.6%	79.4%	98.2%
3: A few times a week	18.0%	11.0%	1.8%	18.4%	10.3%	1.1%
2: A few times a month	9.0%	4.2%	0.5%	7.8%	2.8%	0.4%
1: A few times a year	6.6%	1.8%	0.2%	4.9%	1.3%	0.1%
0: Never	18.9%	8.4%	0.8%	15.3%	6.2%	0.2%
Alternative Measure: *webwork*						
% Internet usage at work	51.7%			59.3%		
Phi Coefficient with *savvy*	0.442			0.464		
Alternative Measure for 2017						
Daily user of smartphone			87.0%			88.6%
Phi. Coeff. with *savvy*			0.461			0.382
Daily user of multi. devices			77.3%			81.0%
Phi. Coeff. with *savvy*			0.361			0.317
Average Age	39.4	42.1	41.0	41.6	44.7	44.7
% Male	46.8%	47.4%	48.2%	62.2%	57.3%	52.9%
% Non-Hsp. White	74.5%	72.7%	65.4%	78.0%	80.7%	71.6%
%Urban	81.2%	77.9%	85.5%	79.2%	72.3%	85.8%
Median HH Income Range	$60,000 - $64,999	$75,000 - $79,999	$75,000 - $99,999	$65,000 - $69,999	$80,000 - $99,999	$75,000 - $99,999
Occupational Distribution						
AC	15.2%	12.9%	12.9%	7.2%	7.5%	9.0%
SS	35.3%	37.4%	30.5%	34.7%	35.8%	26.3%
PM	49.5%	49.7%	56.6%	58.1%	56.7%	64.7%

Source: NHTS (2001, 2009, and 2017).

Table 3. Descriptive statistics on internet-savvy and non-internet savvy work-related trip makers.

	Internet-Savvy					
	2001		2009		2017	
	Non-Svvy	Int.-Svvy	Non-Svvy	Int.-Svvy	Non-Svvy	Int.-Svvy
Observations	27,896	25,851	20,480	66,718	3,000	80,286
Est. Population	48,076,996	43,446,348	24,527,058	71,581,922	3,339,676	98,038,645
Avg. Age	40.3	38.4	44.6	41.3	49.6	40.7
% Male	41.3%	52.9%	41.4%	49.4%	37.6%	48.5%
% College Degree	26.5%	51.9%	19.8%	51.3%	20.7%	53.6%
% Urban	78.6%	84.1%	75.2%	78.9%	79.4%	85.7%
% Savvy						
AC		45.9%		77.8%		96.0%
SS		34.7%		60.9%		94.1%
PM		57.0%		83.8%		98.3%

	Alternative Measures					
	2001		2017		2017	
	Non-Svvy	Web Work	Non-Sphone	SPhone	Non-Multi	Multi
Observations	25,567	28,180	12,477	70,809	18,600	64,686
Est. Population	44,223,900	47,299,444	13,169,044	88,209,278	23,021,093	78,357,229
Avg. Age	39.0	39.9	48.6	39.9	43.1	40.4
% Male	43.0%	50.4%	45.1%	48.6%	43.6%	49.5%
% College Degree	20.3%	55.6%	38.4%	54.6%	33.2%	58.1%
% Urban	78.9%	83.4%	80.2%	86.2%	82.7%	86.3%
% Savvy						
AC		59.0%		83.0%		75.3%
SS		27.2%		83.2%		66.8%
PM		66.9%		90.0%		83.4%

Source: NHTS (2001, 2009, and 2017).

Table 4. Heckman selection model results in 2001, 2009 and 2017.

	2001	2001	2009	2009	2017	2017
	Two Separate Models	Heckman Selection Model	Two Separate Models	Heckman Selection Model	Two Separate Models	Heckman Selection Model
	log-linear	Hckmn Main	log-linear	Hckmn Main	log-linear	Hckmn Main
y: ln(Wk-Trip Miles)	(1-D)	(2-D)	(3-D)	(4-D)	(5-D)	(6-D)
Internet Savvy (vs. Non-Savvy)	-0.435	-0.548*	0.188	0.147	-0.555	-1.027
	(0.280)	(0.323)	(0.283)	(0.285)	(0.719)	(0.907)
SS * Savvy	0.224	-0.0251	-0.349	-0.265	0.0863	-0.0978
	(0.309)	(0.368)	(0.328)	(0.346)	(0.848)	(1.105)
PM * Savvy	0.267	0.423	-0.664*	-0.605*	0.705	0.790
	(0.297)	(0.349)	(0.342)	(0.343)	(0.761)	(1.004)
SS (vs. AC)	0.513**	-0.111	0.959***	0.958***	0.312	0.106
	(0.231)	(0.254)	(0.284)	(0.280)	(0.822)	(1.075)
PM (vs. AC)	0.127	-0.646**	0.785***	0.793***	-0.494	-0.891
	(0.232)	(0.254)	(0.303)	(0.302)	(0.744)	(0.986)
Female (vs. Male)	-0.538***	0.0459	-0.342***	-0.379***	-0.276**	-0.200
	(0.0816)	(0.108)	(0.0963)	(0.104)	(0.115)	(0.143)
Age	0.000165	-0.0142***	0.0103***	0.0121***	0.00890**	-0.0132**
	(0.00306)	(0.00384)	(0.00339)	(0.00404)	(0.00426)	(0.00566)
College Degree	-0.292***	-0.421***	-0.0938	-0.0599	-0.0213	-0.570***
	(0.0876)	(0.112)	(0.0994)	(0.106)	(0.129)	(0.177)
Ln(HH Family Income)	0.252***	0.0344	0.423***	0.438***	0.102	0.0380
	(0.0798)	(0.0886)	(0.0857)	(0.0866)	(0.0964)	(0.116)
South	0.292***	0.295***	0.170	0.166	0.311	0.195
	(0.0963)	(0.0889)	(0.135)	(0.134)	(0.193)	(0.192)
Midwest	0.0909	0.135	-0.153	-0.149	0.0681	-0.0386
	(0.116)	(0.106)	(0.166)	(0.166)	(0.208)	(0.202)
West	0.341***	0.300***	0.0245	0.0219	0.0439	-0.0379
	(0.111)	(0.102)	(0.143)	(0.142)	(0.191)	(0.187)
Non Urban (vs. Urban)	0.289***	0.319***	0.310***	0.317***	0.205	0.209
	(0.0947)	(0.0880)	(0.106)	(0.107)	(0.143)	(0.138)
Weekend (vs. Weekday)	-0.132	0.657***	-0.182*	-0.273*	0.271*	1.075***
	(0.0901)	(0.125)	(0.100)	(0.145)	(0.141)	(0.187)
Constant	-0.178	7.701***	-3.152***	-3.941***	0.843	9.264***
	(0.881)	(1.006)	(0.994)	(1.278)	(1.307)	(1.821)
Unweighted Observations	4,662	52,264	8,027	84,695	4,361	82,437
Selected		4,662		8,027		4,361
Not Selected		47,602		76,668		78,076
Population size	8,047,798	88,325,225	8,153,680	92,626,786	4,469,045	100,520,334
F-stats	12.82		9.18		2.25	
Prob. > F	0.000		0.000		0.005	
Correl. Pred. & Obs. (unweighted)	0.258	0.257	0.245	0.246	0.173	0.174
Correl. Pred. Dist & Dist	0.250	0.247	0.218	0.218	0.126	0.132

z: Selection Indicator	Probit (1-P)	Hckmn Selec. (2-P)	Probit (3-P)	Hckmn Selec. (4-P)	Probit (5-P)	Hckmn Selec. (6-P)
Internet Savvy (vs. Non-Savvy)	0.0353	0.0216	-0.190	-0.190	0.209	0.211
	(0.0976)	(0.0971)	(0.135)	(0.135)	(0.233)	(0.231)
SS * Savvy	0.155	0.180	0.355**	0.355**	0.0667	0.0654
	(0.110)	(0.110)	(0.148)	(0.148)	(0.290)	(0.287)
PM * Savvy	-0.0509	-0.0373	0.234	0.234	-0.0180	-0.0130
	(0.106)	(0.105)	(0.160)	(0.160)	(0.269)	(0.265)
SS (vs. AC)	0.249***	0.240***	-0.0161	-0.0156	0.0786	0.0768
	(0.0831)	(0.0823)	(0.135)	(0.135)	(0.282)	(0.279)
PM (vs. AC)	0.338***	0.333***	0.0298	0.0298	0.133	0.126
	(0.0827)	(0.0817)	(0.154)	(0.154)	(0.262)	(0.258)
Female (vs. Male)	-0.269***	-0.268***	-0.143***	-0.144***	-0.0440	-0.0471
	(0.0307)	(0.0304)	(0.0351)	(0.0351)	(0.0330)	(0.0329)
Age	0.00691***	0.00717***	0.00686***	0.00685***	0.00837***	0.00831***
	(0.00110)	(0.00109)	(0.00136)	(0.00135)	(0.00112)	(0.00111)
Afro-Amrcn. (vs. Non-Hsp W)	0.000581	0.0210	-0.234***	-0.230***	-0.0751	-0.0282
	(0.0693)	(0.0525)	(0.0808)	(0.0822)	(0.0731)	(0.0561)
Asian (vs. Non-Hisp White)	-0.249**	-0.215**	-0.347***	-0.356***	-0.152**	-0.142***
	(0.107)	(0.0842)	(0.0854)	(0.0802)	(0.0641)	(0.0504)
Hisp. or Latn. (vs. Non-Hsp W)	-0.103*	-0.0567	-0.139**	-0.142**	-0.103*	-0.0618
	(0.0605)	(0.0435)	(0.0565)	(0.0569)	(0.0550)	(0.0403)
Other (vs. Non-Hisp White)	0.184**	0.161***	0.0762	0.0766	-0.00952	0.0252
	(0.0835)	(0.0610)	(0.0943)	(0.0966)	(0.0956)	(0.115)
College Degree	0.0803**	0.0825**	0.137***	0.137***	0.243***	0.247***
	(0.0340)	(0.0337)	(0.0371)	(0.0371)	(0.0391)	(0.0384)
Ln(HH Family Income)	0.0702**	0.0692**	0.0527*	0.0527*	0.0165	0.0210
	(0.0281)	(0.0275)	(0.0297)	(0.0297)	(0.0245)	(0.0247)
Weekend (vs. Weekday)	-0.357***	-0.359***	-0.363***	-0.363***	-0.325***	-0.324***
	(0.0340)	(0.0337)	(0.0381)	(0.0381)	(0.0381)	(0.0379)
Constant	-2.448***	-2.452***	-2.124***	-2.124***	-2.552***	-2.612***
	(0.324)	(0.316)	(0.353)	(0.353)	(0.361)	(0.362)
Unweighted Observations	52,302	52,264	84,695	84,695	82,437	82,437
Selected		4,662		8,027		4,361
Not Selected		47,602		76,668		78,076
Population size	88,325,225	88,325,225	92,626,786	92,626,786	100,520,334	100,520,334
Log Pseudo Likelihood	-2.59.E+07	-4.01.E+07	-2.66.E+07	-4.15.E+07	-1.77.E+07	-2.60.E+07
Wald Chi2	340.85	120.57	282.97	88.29	233.03	68.82
Prob. > Chi2	0.000	0.000	0.000	0.000	0.000	0.000
F-stats	24.34	8.61	20.21	6.31	16.64	4.91
Prob. > F	0.000	0.000	0.000	0.000	0.000	0.000
Correl. Pred. & Obs. (not weighted)	0.163	0.163	0.145	0.145	0.105	0.105
Heckman Model Statistics						
ρ		-0.937		0.200		-0.921
		(0.0107)		(0.197)		(0.0219)
σ		2.807		1.535		3.019

	(0.115)	(0.0548)	(0.224)
λ	-2.630	0.307	-2.781
	(0.135)	(0.311)	(0.269)
Wald Test of Indep. Eq. (ρ=0) Chi2	383.4	0.980	122.7
Prob > Chi2	0.000	0.323	0.000

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Distance predictions are made only for those who traveled.

1

Table 5. Marginal Effects of Internet Savvy in 2001, 2009, and 2017.

	2001		2009		2017	
	Two Separate Models	Heckman Selection Model	Two Separate Models	Heckman Selection Model	Two Separate Models	Heckman Selection Model
	log-linear	Hckmn Main	log-linear	Hckmn Main	log-linear	Hckmn Main
y: ln(Wk-Trip Miles)	(1-D)	(2-D)	(3-D)	(4-D)	(5-D)	(6-D)
AC	-0.435	-0.548*	0.188	0.147	-0.555	-1.027
	(0.280)	(0.323)	(0.283)	(0.285)	(0.719)	(0.907)
SS	-0.211	-0.573***	-0.161	-0.118	-0.469	-1.125*
	(0.140)	(0.176)	(0.181)	(0.190)	(0.461)	(0.655)
PM	-0.168	-0.125	-0.475***	-0.458**	0.150	-0.237
	(0.103)	(0.135)	(0.200)	(0.199)	(0.249)	(0.444)
	Probit	Hckmn Selec.	Probit	Hckmn Selec.	Probit	Hckmn Selec.
z: Selection Indicator	(1-P)	(2-P)	(3-P)	(4-P)	(5-P)	(6-P)
AC	0.0353	0.0216	-0.190	-0.190	0.209	0.211
	(0.0976)	(0.0971)	(0.135)	(0.135)	(0.233)	(0.231)
SS	0.191***	0.201***	0.165***	0.165***	0.276	0.276
	(0.0516)	(0.0512)	(0.0638)	(0.0638)	(0.176)	(0.173)
PM	-0.0156	-0.0157	0.0442	0.0444	0.191	0.198
	(0.0410)	(0.0406)	(0.0845)	(0.0845)	(0.136)	(0.133)

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

1 Table 6. Robustness Check by Using Alternative Measures of Internet Usage

	2001-WebUse		2009-WebUse		2017-WebUse		2001-WebWork		2017-SPhone		2017-Multi	
	Two Step Models	Heckman Selection Model Hckmn Main	Two Step Models	Heckman Selection Model Hckmn Main	Two Step Models	Heckman Selection Model	Two Step Models	Heckman Selection Model Hckmn Main	Two Step Models	Heckman Selection Model	Two Step Models	Heckman Selection Model Hckmn Main
y: ln(wk-trip miles/day)	log-linear (R1-D)	(R2-D)	log-linear (R3-D)	(R4-D)	log-linear (R5-D)	Hckmn Main (R6-D)	log-linear (R7-D)	(R8-D)	log-linear (R9-D)	Hckmn Main (R10-D)	log-linear (R11-D)	(R12-D)
Avg Marg. Eff. of Int Use												
AC	-0.0778	-0.258**	0.0485	0.0465	-0.0892	-0.117	0.0202	-0.314	-0.397	0.062	-0.366	-0.181
	(0.101)	(0.115)	(0.0858)	(0.0902)	(0.238)	(0.447)	(0.306)	(0.350)	(0.356)	(0.458)	(0.346)	(0.430)
SS	-0.00543	-0.122**	-0.00736	0.00754	-0.350	-0.785***	0.301**	-0.273	-0.326	-0.527	0.164	0.171
	(0.0415)	(0.0555)	(0.0602)	(0.0619)	(0.225)	(0.264)	(0.135)	(0.173)	(0.234)	(0.346)	(0.272)	(0.349)
PM	-0.0467	-0.0601	-0.243***	-0.238***	0.243*	0.00102	-0.129	-0.138	0.343*	0.0316	0.157	0.0216
	(0.0403)	(0.0543)	(0.0743)	(0.0766)	(0.143)	(0.206)	(0.114)	(0.146)	(0.202)	(0.302)	(0.174)	(0.241)
Occupation FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Female (vs. Male)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Age	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
College Degree	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ln(HH Family Income)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Non Urban (vs. Urban)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weekend (vs. Weekday)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Unweighted Observations	52,302		84,695		82,437		4,662		4,361		4,361	
Population size	8,047,798		8,153,680		4,469,045		8,047,798		4,469,045		4,469,045	
F-stats	11.54		9.30		2.55		11.88		2.71		2.35	
Prob. > F	0.085		0.000		0.001		0.000		0.001		0.003	
Correl. Pred. & Obs.	0.259	0.258	0.245	0.245	0.175	0.176	0.259	0.258	0.171	0.175	0.173	0.174

Correl. Exp(Pred. lnDist) & Dist	0.109	0.112	0.110	0.110	0.016	0.020	0.243	0.243	0.123	0.134	0.133	0.140
z: Selection Indicator	Probit (R1-P)	Hckmn Selec. (R2-P)	Probit (R3-P)	Hckmn Selec. (R4-P)	Probit (R5-P)	Hckmn Selec. (R6-P)	Probit (R7-P)	Hckmn Selec. (R8-P)	Probit (R9-P)	Hckmn Selec. (R10-P)	Probit (R15-P)	Hckmn Selec. (R16-P)
Avg Marg. Eff. of Int Use												
AC	0.00649**	0.0673	-0.00110	-0.0104	0.00113	0.0184	0.0127	0.143	-0.0122	-0.161	-0.00397	-0.0546
	(0.00263)	(0.0278)	(0.00571)	(0.0535)	(0.00834)	(0.117)	(0.00890)	(0.101)	(0.0127)	(0.148)	(0.00986)	(0.131)
SS	0.00866***	0.0572***	0.00838***	0.0561***	0.0147**	0.188***	0.0423***	0.244***	0.00987	0.141	0.00087	0.0141
	(0.00253)	(0.0158)	(0.00302)	(0.0200)	(0.00592)	(0.0725)	(0.00929)	(0.0518)	(0.00706)	(0.103)	(0.00647)	(0.0823)
PM	0.00102	0.00668	0.00245	0.0145	0.0118**	0.119**	0.00122	0.00615	0.0127**	0.130*	0.00680	0.0716
	(0.00270)	(0.0152)	(0.00526)	(0.0309)	(0.00544)	(0.0522)	(0.00788)	(0.0439)	(0.00590)	(0.0670)	(0.00559)	(0.0580)
Occupation FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Female (vs. Male)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Age	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Racial Ethnic Groups	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
College Degree	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ln(HH Family Income)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weekend (vs. Weekday)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Unweighted Observations	52,302	52,264	84,695	84,695	82,437	82,437	52,302	52,264	82,437	82,437	82,437	82,437
Selected		4,662		8,027		4,361		4,662		4,361		4,361
Not Selected		47,602		76,668		78,076		47,602		78,076		78,076
Population size	88,325,225	88,288,533	92,626,786	92,626,786	100,520,334	100,520,334	88,325,225	88,288,533	100,520,334	100,520,334	100,520,334	100,520,334
Log Pseudo Likelihood	-2.58.E+07	-4.01.E+07	-2.66.E+07	-4.15.E+07	-1.77.E+07	-2.60.E+07	-2.58E+07	-4.01E+07	-1.77E+07	-2.60E+07	-1.77E+07	-2.60E+07
Wald Chi2	351.4	116.1	243.0	91.6	242.0	73.5	346.43	108.07	234.13	69.82	236.86	69.24
Prob. > Chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F-stats	25.1	8.29	17.35	6.54	17.28	5.25	24.74	7.72	16.72	4.99	16.92	4.95
Prob. > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Correl. Pred. & Obs.	0.165	0.164	0.145	0.145	0.105	0.105	0.170	0.169	0.106	0.106	0.105	0.105

Heckman	Model						
Statistics:	ρ	-0.937	0.203	-0.921	-0.935	-0.918	-0.923
		(0.0108)	(0.192)	(0.0218)	(0.0110)	(0.0229)	(0.0217)
	σ	2.814	1.534	3.017	2.796	2.986	3.033
		(0.116)	(0.0547)	(0.223)	(0.115)	(0.225)	(0.225)
	λ	-2.637	0.311	-2.778	-2.616	-2.740	-2.798
		(0.136)	(0.304)	(0.267)	(0.136)	(0.272)	(0.270)
Wald Test of (rho=0)	Chi2	376.3	1.050	123.9	374.8	117.2	121.7
	Prob > Chi2	0.000	0.305	0.000	0.000	0.000	0.000

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