1	REDUCING GREENHOUSE GAS EMISSIONS FROM LONG-DISTANCE TRAVEL
2	<b>BUSINESS: HOW FAR CAN WE GO?</b>
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22	Transportation Research Record, 2021 https://doi.org/10.1177%2F03611981211036682
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24	ABSTRACT
25	Long-distance (LD) travels account for over 30-percent of person-trip miles, with energy
26	emissions impacts for everyone. Long-distance business travel can often be handled remotely

and emissions impacts for everyone. Long-distance business travel can often be handled remotely, so 27 targeting such trips for cost, time, and emissions savings may be a wise strategy for protection of climate, budgets, and human health. To better appreciate Americans' LD travel choices, a 73-question online 28 survey was conducted in 2019 that captured 2,327 long-distance (over 200 mileseach way) trips made by 29 929 respondents over the prior 12 months, of which 490 round-trips were for business purposes. 30 Predictive models for LD trips per adult per year, overnights, LD travel times, and willingness to 31 participate remotely and/or pay carbon taxes for those trips were developed using only respondents in 32 Austin. As expected, those with higher education tend to travel more often - for both business and non-33 34 business purposes, everthing else constant. Persons who travel long-distance more frequently are more likely to spend more nights at their destinations, while spending less time in transit/en route. Those 35 from households with more workers and those with fewer children at home tend to be more receptive 36 to having their employers pay carbon taxes. Some level of viability is found in approximately a 37 quarter of the 298 long-distance business trips made by Austinites, and the respondents are willing to 38 remotely participate in 44% of them. In other words, Austinites are willing to remotely participate in 39 40 slightly over 10% of their business trips overall. This is definitely not enough to address carbon emissions in the LD travel sector. 41

- 42
   43 Keywords: Long-Distance Travel, Business Travel, Carbon Tax, Greenhouse Gases, Remote Participation, Travel Behaviors
- 44 45 INTRODUCTION

46

1 Though relatively infrequent, long-distance (LD) travels account for a significant portion of transportaton's

2 vehicle-miles traveled (VMT) and greenhouse gases (GHG) (Georggi and Pendyala, 2000). According to 3

the U.S. 2009 National Household Travel Survey (USDOT, 2009), 75% of all person-trips made in the US 4

were less than 10 miles (one way), accounting for 28.9% of VMT, while trips over 100 miles (one way) 5 made up less than 1% of all vehicle trips but contributed 15.5% of household-based VMT (Schiffer, 2012,

6 Llorca et al., 2018). Looking at all personal travel (including airline, bus and train travel), long-distance

7 travel delivers around 30% of U.S. person-miles (Aultman-Hall, 2018). Average trip lengths and the

8 number of LD trips per person are rising over time in other countries as well (Dargay and Clark, 2012).

9 And in Europe, long-distance trips (counted as those over 100 km or 62.1 mi) constitute about 50% of

10 person-miles (Rich and Mabit, 2011).

11 According to Chester (2008), the GHG life-cycle impact contributions per PMT of different planes are shown

12 in Table 1.

#### 13 14 Table 1. GHG Life-Cycle Impact Contribution by Type of Aircraft

Type of Aircraft	GHG (g/PMT)
Embraer 145	290
Boeing 737	210
Boeing 747	320

15 Air travel is experiencing an increasing trend not only in the United States, but around the world as well.

16 Chi and Baek (2013) found that US air passenger-miles increased 52% for international and 32% for

17 domestic flights between 1996 and 2010, while Mayor and Tol (2010) predicted that from 2000 to 2025,

18 an average annual growth rate of 6.8% is to be observed in passenger kilometers worldwide, and a 5.2%

19 from 2000 to 2050.

20 Trip purposes of tourism (or leisure) and business are key to understanding LD travel (Koenker, 2003; 21 Millán et al., 2016). Travel & tourism GDP summed to \$4,740 billion globally in 2015, with 23.4% of that 22 for business reasons (Turner & Freiermuth, 2016). In the US, year-215 business travel was 28.4% of the 23 US travel and tourism total (Statista, 2016). In general, the goal of leisure trips is to be there, at one's 24 destination. Physical participation is typically fundamental to tourism and leisure, including visiting family 25 members or friends. In contrast, business trips are typically designed to exchange information, 26 professionally network, and/or conduct deals. These goals can regularly be achieved by other means, thanks 27 to conference call technologies and advances in high-speed internet and audio-visual optioins. Video calls 28 allow us to communicate effectively with high definition with almost no time delay. Remote participation 29 requires significantly less time, energy, and resources than business travel, so it is the focus of this study, 30 in terms of reducing LD travel while saving energy, emissions, and other resources.

31 Travel is a major cost for businesses and their workers workwide. For example, the World Travel and 32 Tourism Conference (WTTC, 2015) estimates that U.S. business travel's contribution to GDP is over \$200 33 billion annually, making it 30% of all U.S. travel and tourism expenditures. On average, U.S. companies 34 spend \$949 per worker pursuing a domestic trip (Certify, 2019). LD travel, represented in large part by air 35 travel, is responsible for a disproportionate share of environmental impacts. Airline mode dominates for 36 person-trips over 500 miles, and accounts for more than 90% of mode share at travel distances over 1,000 37 miles (Moeckel et al., 2015.) Airlines' energy and emissions implications per person-mile are typically 38 higher than those of ground travel, with each commercial airline's seat-mile responsible for roughly the 39 same amount of GHG emissions (over 400 gm per mile) as a mid-size sedan, which typically carries 2 40 persons (on average) during long-distance trip-making. (Chester and Horvath, 2009; Hoyer et al., 2001; 41 Ottelin et al., 2014). By filling all seats in most light-duty passenger vehicles, one can reduce one's carbon 42 footprint by 75%, versus flying. By using a small sedan (rather than a large SUV or pickup truck, for example) with hybrid drivetrain or battery power, GHG emissions fall even further, under almost all
 settings. Right-sizing and sharing of electric self-driving vehicles may reduce those numbers further (Lee
 and Kockelman 2019; Loeb et al., 2018; Liu et al., 2017; Michalek et al., 2018; Nichols et al., 2015; Reiter

4 and Kockelman, 2017), but widespread adoption of such technologies is simply not possible in the near

- 5 term. In order to reduce the environmental, cost and other impacts of LD passenger travels in the near and
- 6 long terms, it is important to have a deeper understanding of what motivates such travel.

# 7 **LITERATURE REVIEW**

Key variables impacting LD trip frequency, distance, mode choice, and destination include a traveler's
household income (Van Wee et al., 2006; Sandow & Westin, 2010), age (Collia et al., 2003), education
level (Holz-Rau et al., 2014), presence of children in the household (LaMondia et al., 2016a), and so forth
(Cho, 2013). Specific events and objectives – like professional conferences and vacation opportunities,
friends' weddings and family funerals, tennis tournaments and music concerts (Yang et al., 2016; Burke &

- 13 Woolcock, 2013; McKercher et al., 2008; Aguilera, 2008) regularly motivate LD travel for many different
- 14 types of people.

Regional models of statewide and nationwide trip-making have sought to evaluate the LD travel impacts
for regions and nations (Erhardt et al., 2007; Rohr et al., 2013; Bernardin Jr et al., 2017; LaMondia et al.

17 2016b; Perrine et al., 2017) and can be used to plan the transportation network required in a certain region.

18 Models of LD travelers' mode choices were also developed to estimate the modes used for LD travels and

19 the decision-making process of LD travelers (Scheiner, 2010; Reichert & Holz-Rau, 2015.) LD travels

20 made at different times of day (e.g. day-time or overnight) are known to have different characetristics. Thus,

LD travels carried out at different times of day were studied as well (Aultman-Hall et al., 2015; Sullivan et

22 al., 2016.)

23 As previously mentioned, tourism and business travels are the two most popular types of LD travels.

Tourism and leisure travel occur more frequently in urban areas and in holiday seasons (Große et al., 2019.)

25 Tourism is generally accompanied with aviation and accounted for 8% of global GHG emissions between

26 2009 and 2013 (Lenzen et al., 2018.) Although tourists distinguished their travel to daily commute and

- 27 considered it occasional, some of them still refused to be responsible to the transport of aircrafts and identify
- it as a personal responsibility (Becken, 2007.) Therefore, rather than passing the responsibilities to individual tourists, environmental policies and strategies to mitigate the GHG implications from tourism

30 should target the development of the tourism industry to reduce the global environmental impact and

decarbonize the industry (Cavallaro et al., 2017; Scott et al., 2016; Brendehaug et al., 2017; Gössling et al.,

32 2017).

33 Another type of LD travel, business travel, is more economically motivated and industrialized than tourism,

34 which is more leisure-based. Business travel usually consists of visiting certain business sites, meeting with

35 business counterparts, or contracting to business activities. With economic growth, the significance of

36 business travel will become more important than ever before (Kulendran & Wilson, 2000; Baker et al.,

37 2015.) However, it is possible that travelers on LD business travel might be not as motivated to be

- 38 environmentally concious as non-business LD travelers.
- 39 One of the factors that affects LD business travelers' behavior is that their travel expenses can be reimbursed

40 from their employers (Schaeffer, 2009; Cai et al., 2011); thus, they might be less aware of their implications

41 on society and the environment. Moreover, frequent LD business travelers are usually highly educated,

42 have higher income, status and position in their organization; thus, it is not straightforward to manage and

43 control their behavior (Gustafson, 2012). An in-depth interview revealed that some frequent business

- 44 travelers even consider their experience as a passenger as "moments of relaxation" or "time off," although
- 45 they identify their activities and destination as job-related (Unger et al., 2016). The characteristics of LD 46 business travels have an inherently aggressive impact on the environment by means of GHG emissions.

1 In an effort to reduce the environmental implications and travel costs caused by business LD travels, new

2 communication methods and transport modes have been developed or will be applied in due time. For

3 instance, videoconferencing technologies and remote participation can not only connect people from a long

4 distance without an actual travel but can also allow for communication between groups in different time 5 zones (Julsrud et al., 2012; Pawlak et al., 2015). Proponents of video-conferencing note that it can eliminate

6 the necessity of business air travel by allowing a face-to-face meeting without physically meeting (Lu &

7 Peeta, 2009; Denstadli et al., 2013).

Application of new technologies - including connected and autonomous vehicles, shared autonomous vehicles, and dynamic ride-sharing en route can help reduce the energy intensity of LD travel, while keeping departure times more flexible, travel costs low, and access direct between origins and destinations (LaMondia et al., 2016b; Perrine et al., 2017). But large-scale adoption of self-driving vehicles will not be reasonable until the 2030s and 2040s or 2050s in mode locations (Quarles, 2018), and and range limitations on all-electric vehicles (He et al., 2019; Loeb et al., 2018) makes it difficult to be a feasible option for LD

14 travel in short term.

# 15 DATA DESCRIPTION

16 In March 2019, an online survey was conducted to collect information on American adults' "long-distance" 17 (over 200 miles, each-way) travel behaviors, opinions, and demographics, including numbers of LD 18 business and non-business trips taken over the prior 12 months. LD trip purposes, durations, origins and 19 destinations, cost and other attributes were recorded, as shown in Figures 1 through 3. The initial data set 20 captured 2,327 round-trip LD trips (total) made by 929 respondents (age 18 years or older), with 490 (21%) 21 trips for business purposes. Due to sample advertising via largely Austin-based and UT Austin Parking 22 Services distribution channels, the majority of data came from residents of the Austin, Texas region and 23 those with parking passes at the University of Texas at Austin. To ensure more reliable estimates with 24 robust sample expansion, only data provided by Austin area residents are used in this paper, resulting in n 25 = 1,599 LD trips made by 623 respondents, out of which 298 (18.6%) were for business purposes. Using 26 either sample (n = 929 or n = 623 respondents), the average number of LD trips per respondent per year is 27 about 2.5. While Austinities tend to be more educated than the the average American, they appear similar 28 in LD trip-making frequency.

29 To correct for sampling biases within the Austin region, the 2017 American Community Survey (ACS)

30 splits by household income, gender, age, marital status, education, and ehtnicity (for adults only) were

31 compared to sample demographics, as shown in Figs. 1(a) through 1(f), and then used to weight and thus

32 correct for all values presented elsewhere in this paper, including model estimation for parameter

33 predictions and other results.





45 to

Sample SAustin

(c) Age

35 to



(b) Gender







1

30.0%

25.0%

20.09

15.0%

10.0%

5.0%

18 to 24

# 2 Figure 1. Demographics in Sampled Data versus Austin's Adult Population

65 Or

55

As shown in Fig. 1, survey respondents tend to be of higher income, younger, more often female, single, highly educated, and Caucasian than the average Austin-region adult. Their households' average vehicle ownership is 1.66, which is 16% lower than the national average of 1.97 vehicles per household, according to the 2017 National Household Travel Survey (FHWA, 2018). Females are clearly over-represented in the sample (at 67.8% of respondents vs. 49.8% of the Austin population). To overcome such sampling bias, all survey responses are weighted here by using the American Community Survey (ACS) Public Use 1 Microdata Sample (PUMS) demographic shares for the Austin area. The weights were obtained by 2 subcategorizing both the PUMS data and the survey sample into 288 groups, across 6 age classes, 2 genders,



3 6 educational attainment levels, and 4 marital status classifications.

7 8

(b) Long-Distance Trip Departure by Travel Purpose

# 9 Figure 2. Long-Distance (>200 mile each way) Round-Trip Counts by Business/Non-Business 10 Purposes (using unweighted Austin sample)

- 11 Figure 2(a) shows weighted LD trip fractions for business and non-business trips across 623 respondents,
- 12 with 55.2% of respondents reporting no LD business trips (over 200 miles [each way]) in the 12 months
- 13 prior to the survey and 1.09% reporting no non-business LD trips over the past 12 months. Among all 5,057

1 LD trips reported by Austinites, 77.9% are non-business purposes, while 22.1% are for business purposes.

2 To save on GHG emissions and LD travel costs, it would be useful to forego non-business trips, at at least 3 shorten their distances and lower their per-mile carbon footprints, but technology for remote participation

4 is not an option for almost all personal trips.

5 In terms of trip-making seasonality, Georggi and Pendyala (2000) noted how business trip counts fall

- 6 considerably between October and December, while Mallett (1999) found US non-business LD travel
- 7 peaking over the Thanksgiving (late November), Christmas (late December), and New Year's holidays,
- 8 thus lagging the drop in business trip-making by about 1 month.

9 Figure 2(b) shows month of departure for 1,599 LD trips made by Austinites, with higher fractions 10 ofbusiness trips (versus non-business LD trips) made in February, March, January and November. 11 December alone claims over one-fifth of all non-business trips, while February claims over a quarter of the 12 year's LD business trips. Consecutive months that claim nearly half of all reported LD business-trip 13 departures are January, February, and March, versus December, January, and February for Austinites' non-

14 business departures.

The average reimbursement share for the data set's 489 business trips is 72%. Interestingly, 19% of LD business trips received zero reimbursement, while 44% were fully reimbursed. Roughly one-third of all these LD business trips are less than 300 miles in one-way, Euclidean (straight-line) distance, with travelers spending an average of 6.2 days and 5.2 nights on each, with very high variability (coefficients of variation

19 of almost 4), as shown in Tables 2 and 3.

20

#### 21 Table 2. Hours Spent by Different Modes during Long-Distance Business Trips

Variable	#Obs.	Mean	Std. Dev.	Min	Max	Median
Hours Stopped to Destination	287	1.111 hr	4.169 hr	0 hr	72 hr	0.25 hr
Hours by Air to Destination	287	3.196	3.581	0	45	3
Hours Drive Alone to Destination	284	0.774	1.264	0	9	0
Hours Carpool to Destination	288	0.737	2.417	0	19	0
Hours by TNC* to Destination	287	0.326	1.533	0	30	0
Hours by Train to Destination	287	0.065	0.270	0	2	0
Hours by Bus to Destination	287	0.105	0.516	0	5	0
Hours by Walk to Destination	287	0.049	0.362	0	8	0
Hours by Other Mode(s) to Destination (including airport shuttles, recreational vehicles, and rental cars)	288	0.097	0.981	0	18	0
Hours Stopped on Return Trip	275	1.216	3.016	0	24	0.05
Hours by Air on Return Trip	275	3.015	3.582	0	45	3
Hours Drive Alone on Return Trip	273	0.963	2.079	0	17	0
Hours Carpool on Return Trip	275	0.510	1.426	0	13	0
Hours by TNC* on Return Trip	274	0.399	1.854	0	30	0
Hours by Train on Return Trip	275	0.049	0.224	0	2	0
Hours by Bus on Return Trip	275	0.117	0.551	0	5	0
Hours Walk on Return Trip	275	0.020	0.093	0	1	0

Hours by Other Mode on Return Trip (Including airport shuttle, recreational vehicle, and rental car)2750.0951.017019	0	
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1 \*Note: TNC = ride-hailing trips (like Lyft & Uber)

# 2 Table 3. LD Business Travel Cost Breakdown

Variable	#Obs.	Mean	Std. Dev.	Min	Max	Median
Food Expenses	277	\$ 174.83	\$ 266.29	\$ 0	\$ 6000	\$ 120
Accomodation	278	518.32	680.32	0	6300	300
Administration	276	191.18	530.66	0	4000	0
Visa/Passport	278	6.32	43.06	0	360	0
Transportation	274	354.19	681.06	0	12,000	200
Gas	278	16.43	41.12	0	671	0
Other Cost	278	24.76	246.81	0	3000	0
Reimbursement	268	1023.3	1253.9	0	12,460	720

3

To further understand business trip attributes, travel purposes were asked of all respondents, and multiple choices were allowed. Figure 3 shows those survey results, with "networking" and "fulfillment of job duties" being the top 2 reasons given. Under the response option of "Other", respondents often mentioned the need to perform work-related experiments and tests, rehearse and/or perform sports or music, and pursue legal activities (including depositions and meetings with lawyers and/or judges).



9

#### 10 Figure 3. Trip Purpose Distribution (n=1070)

11 Unfortunately, just 24.9% of Austinites' LD business trips are reported as possibly substitutable via remote 12 participation technologies, with more detailed classification of these 106 responses shown in Table 4. The 13 great majority (75.1%) were deemed "impossible", in terms of remote substitution. Among 383 trips, 114 14 could not be done remotely because the respondents wanted to travel to the destination area apart from their 15 primary trip purpose. Among these 114 trips, 85 indicated that meeting in person was needed to help close 16 a business deal, while 71 cited the lack of infrastructure or technology limitations. Among the other 208 (of 17 the 383 "impossible to substitute") trips, many respondents noted their involving a transfer of property or 18 other activities (like testing in person) that required their physical presence.

8

#Obs. = 106			Total		
		Yes	No	Not sure	Total
Possibility of	Yes	29.2%	39.6%	3.32%	72.1%
Remote Participation	Not sure	14.9%	12.3%	0.67%	27.9%
Total		44.1%	51.9%	3.98%	100%

#### 1 Table 4. Possibility of vs. Willingness to Remotely Participate in LD Business Trips

## 2

# **3 MODELING RESULTS**

4 To appreciate the various factors that make one business traveler answer in one way versus another, 595 5 respondents were first selected, who had experienced long-distance travel (over 200 miles each way) within 6 the last 12 months. Among total 623 Austinites sampled in the survey, 595 respondents were used during 7 the model calibration to best fit the model. The excluded 28 respondents did not have the relevant 8 explanatory variable to fit the model. A negative binomial model was used first, to predict the numbers of 9 business and non-business trips per year, with the base case being a married, full-time employed, 18-to-24-10 year-old male with a bachelor's degree, no children, no pet, an annual household income of \$100,000 to 11 \$124,999, who has someone that needs care at home and household members over 16 that can't drive, in a

12 two-member, two-worker household. The results are shown in Tables 5 and 6.

#### 13 Table 5. Parameter Estimates in Prediction of Number of Business Trips per Year (using

## 14 population-weighted negative binomial count model)

Variable	Coefficient	P-Value
Age 35-44	0.635	0.092
Age 55-64	-0.668	0.038
Household Size $= 5$	-0.894	0.060
Worker in Household = 1	0.456	0.052
Female	-0.492	0.011
Black/African American	-2.297	0.003
2 Children in Household	1.734	0.002
Income \$30,000 - \$49,999	-0.649	0.012
\$60,000 to \$74,999	-0.723	0.073
\$75,000 to \$99,999	-1.373	0.000
High School Diploma	-1.998	0.004
Some College, no Degree	-0.866	0.005
Associate's Degree	-2.455	0.017
PhD Degree	0.735	0.002
Employed, working less than 40 hours per week	-1.585	0.001
Retired	-2.414	0.000
Single	-0.809	0.001
Widowed	-25.881	0.000
No Household Member Requires Special Attention	1.471	0.000
No Household Member over 16 w/ Conditions Prevent Driving	1.459	0.005

Constant	-1.566	0.007
Dispersion Parameter	$2.631 \pm 0.367$	

1 n = 595, Pseudo R2 = 0.1391

2 The most practically significant variable corresponding to a person's making more business trips each year 3 was having two children in household, with an incidence rate ratio (IRR) of 5.66 (meaning that the average

4 expected number of trips per year rose by more than a factor of 5 when this binary variable changed from

5 0 to 1), and the second most significant one was having a PhD degree, with an IRR of 2.09. Being widowed

6 was by far the most significant variable corresponding to fewer business trips, with an IRR of  $5.75 \times 10^{-10}$ 

7 12. Two other key covariates having an associate's degree (which is about 2 years of college coursework)

8 and being retired, with IRRs of 0.086 and 0.089, respectively, suggesting 91% fewer business trips each 9

year for persons of that type, everything else constant. This result supports the notion that highly educated

10 workers living in larger households are more likely to have more business trips than others.

#### 11 **Table 6. Negative Binomial Model Output for Non-Business Trips**

Variable	Coefficient	P-Value
Age 45-64	-0.319	0.003
Household Size $= 3$	-0.339	0.018
3 Workers in Household	0.314	0.040
4 Workers in Household	-1.269	0.001
Black/African American	-0.319	0.024
Asian/Asian American	-0.321	0.014
1 Child in Household	0.316	0.068
Income \$75,000 to \$99,999	0.251	0.026
Income \$150,000 to \$199,999	0.417	0.006
Income \$200,000 or more	0.538	0.000
High School Diploma	-0.904	0.000
Some College, No Degree	-0.215	0.083
Employed, working less than 40 hours per week.	-0.652	0.005
Student, working part time.	0.639	0.000
Student, not working.	0.750	0.000
No Household Member Requires Special Attention	0.313	0.018
No Household Member over 16 w/ Conditions Prevent Driving	0.543	0.066
Not Sure on Household Member over 16 w/ Conditions Prevent	0.997	0.008
Driving	0.777	0.000
Constant	0.848	0.005
Dispersion Parameter	$0.366 \pm 0$	0.046

12 n = 595, Pseudo R2 = 0.0644

13 The most practically significant variable associated with more non-business trips each year comes with 14 being an unemployed student, with an IRR of 2.12, followed by being a student working part-time, with an 15 IRR of 1.89. Some other important variables (leading to more LD non-business trip-making each year) 16 include having an annual household income higher than the base case and having one child in the household. 17 The most significant variables associated with *fewer* non-business trips are having only a high school 18 diploma (no higher degrees) and being part-time employed, with IRR values of 0.40 and 0.52, respectively. 19 Having a household size of 3 persons also corresponds to a lower model-predicted number of non-business 20 trips. This result supports that idea that those with fewer household members are more likely to have non-

21 business trips than others.

1 The number of nights spent at one's destination of each business trip was predicted by fitting another 2 negative binomial model, as shown in Table 7. Compared to the base case, having an associate's degree, an 3 annual household income between \$20,000 and \$39,000, or traveling long-distance for work 5-8 times a 4 year were more likely to be identified with more nights spent at the destination. On the other hand, having 5 a high school diploma, age being over 24, and having 2 children in household were more likely to be 6 identified with less nights spent at the destination. Overall, the more often the individual travels, the more 7 nights he/she is likely to spend at the destination of his/her trips. The respondents were also more likely to 8 spend more nights at their destination if their destination was located farther than 300 miles in straight-line

9 distance from their origin.

Variable	Coefficient	P-Value
Annual Long Distance Trips Made	0.011	0.006
Age over 24	-1.564	0.000
2 Children in Household	-0.632	0.006
3 Children in Household	0.661	0.000
Household Income \$20,000 - \$39,999	1.181	0.000
High School Diploma	-2.152	0.000
Associate's Degree	1.667	0.000
Master's Degree	0.292	0.048
Student, Working Part-Time	-0.570	0.017
Retired	0.708	0.001
Travel Long-Distance for Work 1-4 Times a Year	0.677	0.008
Travel Long-Distance for Work 5-8 Times a Year	0.889	0.000
Trip Longer than 300 Miles Over Land	0.655	0.000
Constant	1.318	0.002
Dispersion Parameter	$0.446 \pm$	0.090

# 10 Table 7. Number of Nights Spent at Business Trip Destinations

11 n = 276, Pseudo R2 = 0.1414

12 Finally, the total travel time (in hours) the respondents spent in their travel was predicted by fitting a linear 13 regression model, both to from their destination, the results are shown in Table 8. Unlike the results shown 14 above, the travel time was shorter if the respondent traveled long-distance trips more often. Positive 15 coefficients that appear to be the most practically significant include having more than 5 vehicles, having 16 an annual household income of \$10,000 - \$19,999 or \$30,000 - \$39,999, while negative coefficients include 17 having 3 children in household, traveling for work 5-8 times per year, and having 1-4 vehicles in 18 household. The number of vehicles owned by a household was especially meaningful, by showing that 19 respondents with 1-4 vehicles tend to have shorter total travel time than respondents with no vehicles, while 20 respondents with 5 or more vehicles tend to have longer total travel time than those with no vehicles.

#### 21 Table 8. Linear Regression Model Output for Travel Time (hr)

Variable	Coefficient	P-Value
More than 20 Long Distance Trips per Year	-2.743	0.048
Household Size $= 1$	2.695	0.010
1 Worker in Household	-1.853	0.078
3 Children in Household	-6.463	0.000
Annual Income \$10,000 - \$19,999	6.884	0.010

Annual Income \$30,000 - \$39,999	5.512	0.000
Student, Working Part-Time	-3.924	0.000
Single	-3.434	0.001
Pet but Do not Need Care While Gone	-2.941	0.000
1 - 4 Vehicles	-5.800	0.001
More than 5 Vehicles	23.839	0.000
Travel for Work 5-8 Times per Year	-6.042	0.000
Constant	18.262	0.000

1 n = 256, R2 = 0.1009

2 After estimating the model to predict the number of trips made per year, the length of travel, and travel 3 time, each Austinite's opinion on carbon tax was estimated to understand how much of the travels can be 4 charged for a carbon tax. An ordered logistic model was estimated to predict the respondent's opinion on 5 charging carbon tax to the companies that require employees to travel longer distance. To avoid carbon tax, 6 companies might reduce unnecessary long-distance trips and replace them to remote participation. In the 7 survey question, five levels of responses included extremely unreasonable, moderately unreasonable, 8 neither reasonable nor unreasonable, moderately reasonable, and extremely reasonable. As shown in Figure 9 4, moderately reasonable gained the highest response rate (40.8%), which implies charging carbon tax to 10 mandatory long-distance travels could be acceptable. The sum of moderately reasonable and extremely 11 reasonable was higher than 60%, which implies that the respondents supports the carbon tax suggested in 12 this paper.



13 14

#### 14 Figure 4. Distribution of Attitudes towards Carbon Tax (n = 586)

15 According to Table 9, respondents from households with more workers may consider carbon tax to be more

16 reasonable, while those with more children in their household are unlikely to consider carbon tax as a

17 reasonable option. Compared to the base case of having a bachelor's degree, one with an associate's degree

18 may also tend to view the carbon tax as less reasonable. This result supports that households with a more

19 productive population favor the carbon tax designed in this paper more so than others.

# 20 Table 9. Ordinal Logistic Model Output for Charging Carbon Tax

Variable	Coefficient	P-Value

Household Size $= 5$	2.640	0.009
Household Size $= 8$	-1.636	0.000
5 Workers in Household	21.100	0.000
7 Workers in Household	0.453	0.000
Mixed/Multiracial Ethnicity	0.856	0.045
1 Child in Household	-1.104	0.041
3 Children in Household	-5.529	0.001
6 Children in Household	-3.711	0.001
Associate's Degree	-1.315	0.020
No Household Member Requires Special Attention	-0.668	0.060
	Threshold	Std. Dev.
Threshold 1 ( $\Psi_1$ )	-2.819	0.364
Threshold 2 ( $\Psi_2$ )	-1.789	0.361
Threshold 3 ( $\Psi_3$ )	-1.226	0.353
Threshold 4 ( $\Psi_4$ )	0.795	0.348

1 n = 574, Pseudo R<sup>2</sup> = 0.0271

# 2 CONCLUSIONS

3 This work obtained extensive data on Austinites' long-distance (over 200-miles each way) trip-4 making for an entire year, and analyzed those data in order to predict number of trips made each year, trip 5 duration, travel time, willingness to pay or have one's employer pay for carbon offsets on such travel, and 6 willingness to shift to remote participation for business trips. Those making more long-distance business 7 trips tend to reside in larger households, while those making more non-business trips tend to have fewer 8 household members. Those traveling more often tend to spend more nights at each trip's destination than 9 others. Those with more workers and less children in the household tend to view carbon-taxation of LD 10 travel more reasonable, as a public policy, than others. Unfortunately, just 25% of all LD trip-making 11 appears to be for business purposes, and thus having reasonable potential for remote participation and 12 significant GHG reductions; and (weighted) respondents for just 10% of the LD business trips observed in 13 this data set were willing to substitute their trip using remote participation technology options. Much 14 greater reduction in LD travel's carbon emissions are needed to achieve climate protection goals equitably 15 in this fast-growing area of GHG emissions. Sharing rides in fully-electric self-driving vehicles, on the 16 ground, rather than in the air, may be key, in addition to LD travelers' avoiding business-class and first-17 class seating and using carbon taxes on all air travel, ground travel and hotel rentals to purchase offsets 18 for things like rainforest protection, investments in renewable energy and well-insulated homes, battery-19 electric fleets, and reforestation efforts.

# 20 ACKNOWLEDGEMENTS

21 The authors are grateful for the contribution of Jeffrey Hahm and classmates in CE 392E, Acquisition & 22 Analysis of Transport Data, at the University of Texas at Austin during the Spring 2019 semester for the 23 development of survey questions and data collection. They greatly appreciate the University of Texas at

Austin's Parking & Trasportation Services leaders for distribution of the online survey URL and to Albert

25 Coleman for his editing and submission support.

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