

The value of time, with and without a smartphone

Joseph Cook and Mary Tiana Randriamaro*

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Abstract

Smartphones can lower the disutility of waiting by enabling productivity and making time pass more pleasantly. We elicit the compensation required by subjects to wait for 30 minutes, alone in an empty room, under four different conditions that varied access to the subject's smartphone. Compared to the treatment where subjects had full use of their phone, we find that they required 24% percent more to wait with the audio features of the phone remaining but the phone physically locked away, 48% percent more to wait with only an FM radio, and 79% percent more to wait in a quiet room.

***Cook**: Associate Professor, School of Economic Sciences, Washington State University, Hulbert Hall, Pullman WA 99164. joe.cook@wsu.edu. **Randriamaro**: Doctoral student, School of Economic Sciences, Washington State University, mary.randriamaro@wsu.edu.

1 Introduction

Valuing changes in how people allocate their time is of central interest in several fields of economics, including transportation (Mokhtarian, 2018), labor (Aguiar et al., 2012), development (Jeuland et al., 2010; Meeks, 2017), and the environment (Fezzi et al., 2014; Lloyd-Smith et al., 2019). In particular, it often plays a critical role in benefit-cost analyses of public investments (Boardman et al., 2018). In Becker (1965)'s seminal time allocation framework, an individual's value of time (VOT) is equal to her wage rate and is uniform in all activities and under all circumstances. This model is useful for valuing changes in the time use of employees while they are on the job, where there is a consensus that the correct opportunity cost of the employee's time is her before-tax market wage, including benefits and indirect costs of employee supervision (Baxter et al., 2017).

Valuing time spent in non-market activities like commuting, recreation, household chores, or caring for family members is more challenging. To tie the value of time only to the wage rate and assume a single value of time savings across sectors is to assume that people receive the same utility from an hour spent waiting in line and an hour spent playing with their children or watching television. It also ignores individual-level heterogeneity in how people perceive the utility or disutility of certain activities. DeSerpa (1971) extended Becker's model to allow the marginal utility (and disutility) of time to vary by the type of activity, implying activity-specific values of time. Despite this, however, analysts in most sectors continue to rely on rule-of-thumb estimates for the value of time spent outside work, typically 50% of after-tax wages (Boardman et al., 2018; Whittington and Cook, 2019). In a recent summary of best practices in implementing recreation demand studies, Lupi et al. (2020) recommend using a fraction between one-third and one-half of household income converted to an hourly rate.

An important exception is the transportation sector, where VOT estimates have long been expected to differ based on the mode and characteristics of travel, particularly the disutility of driving in congested traffic (Truong and Hensher, 1985; Hensher et al., 1990; Hensher, 2001; Small, 2012). Mackie et al. (2001) notes "the characteristics of the journey" as one of six important factors influencing individuals' value of travel time. Although

most studies included in [Abrantes and Wardman \(2011\)](#)'s meta-analysis of UK travel time valuation studies did not distinguish traffic conditions, nine studies contained 29 estimates of the "congestion multiplier". They found that drivers are on average willing to pay 54 percent more to avoid an hour spent in congestion than to avoid an hour spent in free-flowing traffic. (See also Table 1 in [Wardman and Nicolás Ibáñez \(2012\)](#) for a summary of congestion multiplier studies).

In the recreational demand literature, time spent traveling to a site is typically pooled with time spent at the recreation site ([Lupi et al., 2020](#)), and this time may provide recreationists with higher utility than time spent at work or commuting to the office. This intuition and an early influential study ([Cesario, 1976](#)) led researchers to assume a value of recreation-focused travel and on-site time of one-third of hourly wages. A more recent study exploited variation in the time-money tradeoff by asking visitors to Italian beaches whether they drove via faster toll roads or slower but free roads ([Fezzi et al., 2014](#)). They report an average value of time of three-fourths of the wage rate, with significant heterogeneity in these valuations. In the broader context of a study of recreational fishing, [Lloyd-Smith et al. \(2019\)](#) use a stated preference approach to elicit the value of leisure time by asking how much compensation subjects would require to perform an administrative task (sorting papers). Importantly, the task would be performed on a weekend, when subjects would likely be pursuing other leisure activities. They also find significant heterogeneity, with older respondents, those in larger households and the self-employed demanding a higher compensation for forgoing time on the weekend. They find that this individual-specific value of leisure time is approximately 90% of the subject's hourly wage rate, on average, but that the association is in fact quite weak. [Lloyd-Smith et al. \(2020\)](#) finds that fishermen's value of leisure time is 55% higher, on average, during the summer than other seasons.

We focus in this paper on the disutility of time spent waiting, a ubiquitous feature of life. We wait on planes, trains, and automobiles and at stores and clinics. Devices like smartphones or laptops can decrease the disutility of time spent waiting by letting some types of employees accomplish work-related tasks ([Lyons and Urry, 2005](#); [Kouwenhoven and de Jong, 2018](#); [Varghese and Jana, 2018](#); [Malokin et al., 2019](#)) or simply by decreasing

the drudgery of a long train ride or a doctor's office wait. [Ettema and Verschuren \(2007\)](#) found that commuters who listen to music while traveling, for example, have lower WTP to lower commuting times. The majority of the research analyzing the effect of information technology and multitasking on the value of time has focused on public transit. These studies find that technology's ability to make travel time useful increases its utility and thus decreases willingness to pay for shorter travel times ([Ettema and Verschuren, 2007](#); [Frei et al., 2015](#); [Hong et al., 2019](#); [Malokin et al., 2019](#); [Varghese and Jana, 2018](#); [Wyer and Wilson, 2017](#); [Zhou et al., 2018](#)). However, researchers have begun to look at the implication of ICTs on fully automated vehicles (FAV). As when riding in a taxi, riders in an FAV would be able to engage in activities other than driving, which is likely to lower their value of travel time savings ([Fagnant and Kockelman, 2015](#)). A reduced value of travel time savings would have large implications for benefit-cost analyses of roadway and transit infrastructure improvements.

Our contribution is a direct and incentive-compatible test of how the value of time spent waiting changes based on access to smartphone services. A number of studies have used time, rather than money, as the numeraire good in an experimental setting ([Berger et al., 2012](#); [Noussair and Stoop, 2015](#)). We use a Becker-DeGroot-Marschak (BDM) mechanism to elicit subjects' willingness to accept (WTA) for waiting for 30 minutes, alone in an empty room, under four different conditions described in more detail below. Our subjects were recruited from the local community and span a wide age range. We find that one quarter of the respondents did not distinguish between the utility of these four waiting conditions. However, we find that, on average, compared to the baseline waiting condition where a subject had full use of her smartphone, subjects required 24% percent more to wait with the audio features of the phone remaining but the phone physically locked away, 48% percent more to wait with only an FM radio, and 79% percent more to wait in an empty, quiet room. Although the experiment was conducted in a room, the findings are easily applicable to other scenarios where individuals are waiting.

2 Methods

We used the incentive-compatible Becker-DeGroot Marshak Mechanism (BDM) to elicit the minimum amount of money each individual would be willing to accept to wait under four different waiting conditions. In all conditions, the subject would wait alone for 30 minutes in an empty room (but for a few economics textbooks) on our university's campus. The first condition involved waiting with full access to the subject's smartphone and a simple FM radio, but the subject's bag and any other materials she brought were put away in a small locked cabinet. We will refer to this in shorthand as the "Smartphone" condition below, since the subject had full access to her phone. Subjects who were university students, faculty or staff could access the university Wi-Fi network, and cellular reception was good in the room for subjects unaffiliated with the university to access the internet. The second condition involved syncing the subject's smartphone to a high-fidelity bluetooth speaker with the ability to make calls using voice commands or play music, but then locking the phone away in the locked cabinet along with all other materials. We call this the "Bluetooth" condition below, though the subject could also listen to a small FM radio. The third condition ("Radio") further removed the ability to sync the phone to the speaker, leaving the subject with only the FM radio to listen to for the 30 minute wait period. Finally, the fourth condition ("Nothing") removed the FM radio: the subject would wait in the empty room, alone, with no music and nothing to read or do. Our hypothesis was that the disutility of waiting increased across these conditions, with the corresponding WTA for waiting under these conditions also increasing.

After eliciting WTA estimates for each of the four conditions, we then used a computer to randomly generate the experimenter's willingness-to-pay (WTP). This randomly-chosen offer was capped at \$35 (\$70 per hour) for budget reasons, though subjects were not told this upper limit and only four subjects had a WTA that exceeded this limit. We then randomly chose which of the four waiting conditions would be the real condition by having subjects pull a number from a hat. If the randomly-chosen offer was greater than the subjects WTA, the subject would earn the randomly-chosen offer and would actually wait for 30 minutes under that chosen wait condition.

We used two practice rounds to ensure subjects understood the experiment, each time having the subject report his WTA for each of the four conditions, randomly generating our WTP, randomly choosing the waiting condition, and reporting whether he would have actually waited for 30 minutes and his total earnings. The third round was played for real. Appendix Figure A1 shows these average bids (with 95% confidence intervals) did not change appreciably between the two practice rounds and the final round, so we focus only on the offers in the third, real round.

Subjects earned a show-up fee of \$15 for completing these three rounds as well as a short demographic questionnaire. Earnings from the real round ranged between \$9 and \$35 with an average of \$21.25 per subject. The mean total earnings were \$22; the maximum earned was \$50. Fifty-four percent of subjects actually waited, all of whom waited for the entire 30 minutes.

The study was preregistered in the Open Science Framework registry (7/29/2019, osf.io/fj5r8). We solicited participation with flyers, mailers, ads in local newspapers, and classroom announcements. We also had a large local employer post the ad to their internal listserv. We conducted the experiment with 82 subjects, drawn from Washington State University students and staff, and community members of the surrounding community of Pullman, WA and Moscow, ID. We dropped one subject from the analysis because he arrived at the session without a smartphone, and a second subject who reported offers to wait for no compensation and may have misunderstood the task.

3 Results

Forty-three percent of our 80 subjects were students and 72% were female. The median subject was 25 years old; 35% were under 25 years old, 43% were between 25 and 45, and 22% were over 45. Seventy-one percent were employed, 15% were unemployed or searching for work, and 11% were retired. Of those employed, 43% were paid hourly, earning an average wage rate of \$15.98 per hour. The average annual earnings of salaried workers was \$50,657 (median = \$37,500; salaries were asked in ranges). We did not ask questions about work expectations for salaried workers, but assuming each works 40 hours

per week and 52 weeks per year, the average implied hourly wage rate is \$24.35 (median \$18.03). We assume \$12 per hour, the 2019 minimum wage in Washington State, for retired and unemployed subjects.

Each subject's opportunity cost of time spent waiting will of course reflect their differing economic circumstances, and we calculate subjects' offers as a fraction of their hourly wage rate. Our interest, however, is not in estimating the value of waiting time in dollars or as a fraction of wages. We focus on estimating the relative utility and disutility of waiting under different conditions. The key variable of interest is therefore the relationship among each subject's four WTA offers, rather than differences *across* subjects.

The majority of subjects perceived differences in the disutility of waiting under the four different conditions and required different compensation: only one-quarter of subjects asked for the same compensation for all four conditions in the final, real round. The average offer to wait for 30 minutes under the unrestricted "smartphone" treatment during the final, real round was \$11.18 (Table 1). Translated into hourly compensation, this was 180% of the subject's hourly wage, on average. Subjects asked for an average of \$13.21, or 201% of wages, to give up physical access to the smartphone but retain the ability to use bluetooth for calls or listen to music ("bluetooth"). Having access only to FM radio increased mean offers to \$15.63, or 242% of hourly wages ("radio"). Subjects asked for an average of \$17.91, or 265% of wages, to wait in the empty room without a radio or access to the phone ("nothing"). The differences in offers, in dollars or as a percentage of wages were all statistically significant in nonparametric Wilcoxon signed pair tests (Bohm et al., 1997; Cason and Plott, 2014; Kecinski et al., 2018).

Table 1: Monetary compensation required to wait for 30 minutes under four conditions

	Offers			Test of differences		
	Dollars	As percent of hourly wage	As fraction of smartphone offer	Nothing	Radio	Bluetooth
	Mean (se)	Mean (se)	Mean (se)			
Nothing	17.91 (1.49)	269% (35)	1.79 (0.13)	–	–	–
Radio	15.63 (1.42)	245% (40)	1.48 (0.08)	***	–	–
Bluetooth	13.21 (0.97)	204% (29)	1.24 (0.04)	***	***	–
Smartphone	11.18 (0.82)	181% (32)	–	***	***	***
N =	80	80	80			

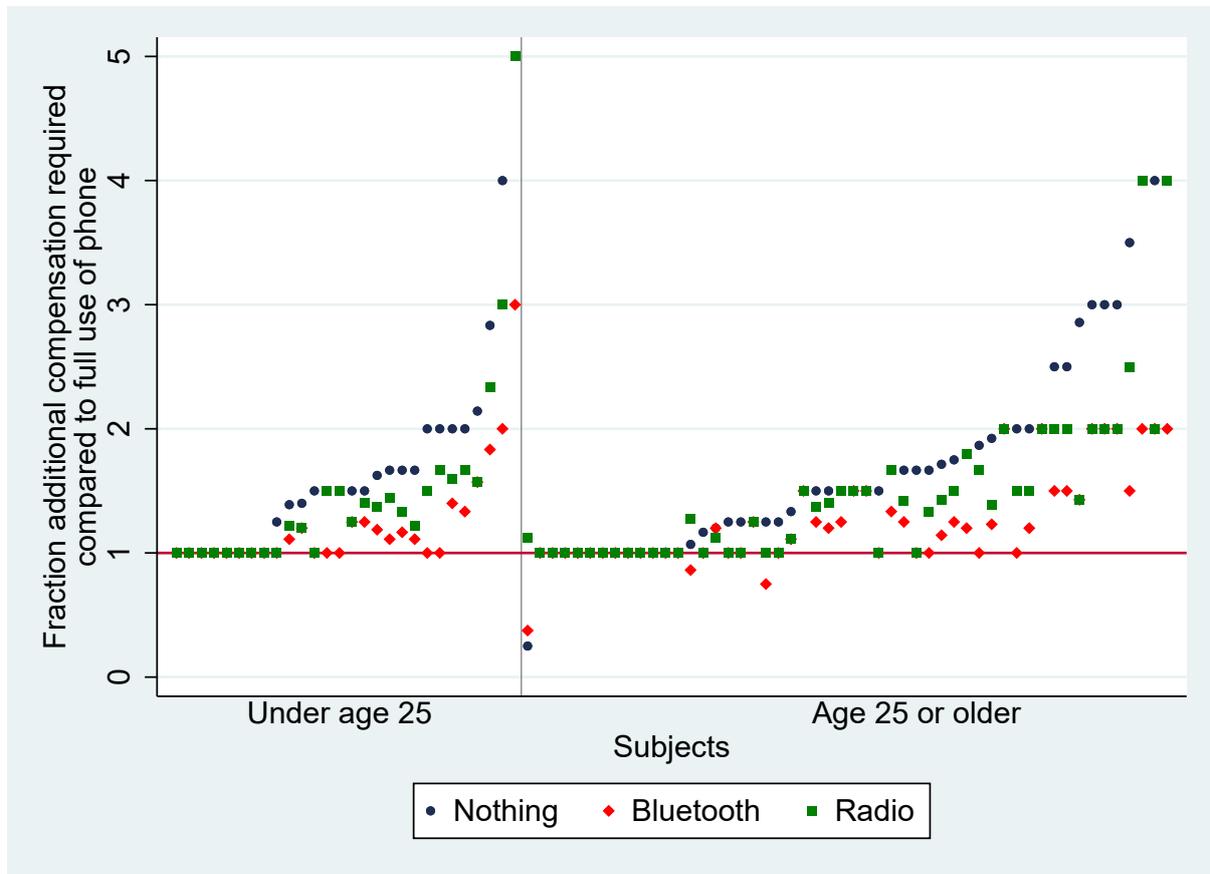
Notes: Test of differences in offers using Wilcoxon signed-rank test, *=significance at the 10% level, ** = 5%, ***=1%. Differences were statistically significant using offers in dollars or as a fraction of hourly wage.

We also transformed the WTA offers for the Radio, Bluetooth, and Nothing conditions as a fraction of the offer for the waiting with full access to their smartphone. This allows one to interpret our results as the additional compensation needed to wait with smartphone services removed. For example, our subjects required 24% more to wait with only the bluetooth components of their phone (and an FM radio) rather than with full use of their smartphone (Table 1). They required 48% more to wait with only an FM radio, and 79% more to wait with nothing.

Different transformations are possible. For example, if one was interested in understanding how the value of time spent traveling alone by automobile may have changed as in-car technology improved, one could use the “radio” condition as the base case. Compared to sitting with access only to an FM radio (as a driver would have experienced before the advent of smartphones), our subjects required 12% less to wait with access to phone services streamed over bluetooth. Our subjects required 24% less than the Radio treatment when they had full access to the smartphone, as they might in a fully-automated vehicle, an estimate we return to in the concluding section.

Returning to our original transformation, Figure 1 plots the fraction of additional compensation needed for waiting with access to Nothing (blue dots), Radio (green squares), and Bluetooth (red diamonds) compared to the full access to a smartphone across all participants. The figure is ordered by the difference in the “nothing” condition, so it also shows the quarter of respondents who did not distinguish between the conditions (the three

Figure 1: Fraction of additional compensation required for access to nothing, radio, and blue-tooth compared to the full use of smartphone, by age.



symbols lie on top of each other). We partition the figure by age. We hypothesized that responses from subjects who have grown up with smartphones would be different from subjects who had not. As the most popular smartphone (the iPhone) was released in 2007, we argue that subjects under the age of 25 have lived mostly in a world with smartphones. We suspected that this younger population would demand higher compensation to wait with restricted access to their smartphone (higher ratios in Figure 1). This pattern is not apparent in the figure, however, and Wilcoxon rank-sum tests showed no statistical difference in the ratios of offers between subjects under and over 25 years old. For example, the mean offer to wait with access to nothing (compared to waiting with full smartphone access) was 1.79 among those both under and over 25 years old. To wait with access to the radio, those under 25 required 48% more than the smartphone condition while those over 25 required 49% more. Subjects under- and over-25 required respectively 26% and 23% more to wait with access only to the bluetooth services.

We formalize these results in a simple pooled OLS model that controls for gender, student status, age (a dummy for under 25 years old) and employment status (Table 2). Standard errors are clustered at the subject level. Model 1 replicates the results from Table 1, showing the effect of the treatment programs on the offers in dollars with no controls. We find no statistically significant impacts on offers for gender, student status, or employment status (Model 2). The pair-wise correlation between a subject's hourly wage rate and her WTA offers is positive but very small in magnitude ($\rho = 0.10$) and marginally statistically-significant ($p=0.06$). The relationship weakens when other controls are added (Table 2). However, [Lloyd-Smith et al. \(2019\)](#) also find a relatively weak relationship: the correlation coefficient between the elicited value of time and the hourly wage rate is only 0.58.

Model 3 explores interactions between demographics and differences among a subject's four WTA offers. Interactions between age, wage rate and gender and "Bluetooth" and "Radio" were generally not statistically-different from zero, though this model likely over-fits our small sample. We do find that women required higher compensation for the Bluetooth waiting condition than men, though the interaction term is only marginally significant.

Finally, Model 4 uses the ratios of each offer divided by the offer for the Smartphone treatment (i.e. the data in Figure 1) rather than offers themselves. The constant of 1.47 can be interpreted to mean that a subject who was male, unemployed or retired, a non-student, and over age 25 required 47% higher compensation, on average, to wait in the "Nothing" condition compared to the "Smartphone condition". He required 24% more to wait with in the Radio condition (calculated as 1.47 minus 0.23), and 9% more to wait with "Bluetooth" compared to "Smartphone". We again find no statistically significant interactions with demographic controls.

Table 2: OLS Model: WTA offers to wait for 30 minutes under four conditions

	(1)	(2)	(3)	(4)
	Offer (dollars)	Offer (dollars)	Offer (dollars)	Percent of offer for Smartphone treatment
Nothing	6.74*** (6.27)	6.74*** (6.21)	4.87** (2.12)	
Radio	4.46*** (4.49)	4.46*** (4.45)	2.84 (1.42)	-0.23** (-2.60)
Bluetooth	2.04*** (4.66)	2.04*** (4.61)	0.76 (0.83)	-0.38*** (-3.27)
under25		-4.93* (-1.88)	-3.62 (-1.41)	-0.098 (-0.37)
Female		-0.83 (-0.37)	-2.16 (-1.17)	0.34 (1.59)
Student		-2.06 (-0.74)	-2.06 (-0.73)	0.12 (0.65)
Salaried		0.22 (0.09)	0.22 (0.09)	0.040 (0.22)
Hourly		0.42 (0.19)	0.42 (0.19)	0.053 (0.26)
Hourly wage rate		0.023 (0.23)	-0.018 (-0.36)	0.0015 (0.22)
Radio X Under 25			-1.83 (-1.41)	0.014 (0.12)
Radio X Wage Rate			0.059 (0.53)	-0.00072 (-0.26)
Radio X Female			1.74 (0.93)	-0.10 (-0.96)
Nothing X Under 25			-2.40 (-1.48)	
Nothing X Wage Rate			0.075 (0.59)	
Nothing X Female			1.98 (0.96)	
Bluetooth X Under 25			-1.01 (-1.35)	-0.020 (-0.10)
Bluetooth X Wage Rate			0.029 (0.69)	-0.0012 (-0.26)
Bluetooth X Female			1.61* (1.93)	-0.19 (-1.19)
Constant	11.2*** (13.49)	13.7*** (5.21)	14.9*** (7.92)	1.48*** (7.10)
Observations	320	320	320	240

Notes: Employment status is captured by dummy variables for whether the subject works on a salaried or hourly basis; the omitted category is equal to one if the subject was unemployed or retired.

To investigate what type of subjects did not distinguish between the utility of the four conditions, we also estimated a probit model where the dependent variable was equal to one if all four offers were the same. Neither gender, age, student status, nor employment status (salaried versus unemployed or retired) were statistically-significant predictors of making four identical offers (results available on request).

Finally, we explored the disutility of waiting by directly asking the 43 participants whose offers were accepted (and who actually waited) how happy they had been “sitting in the room for 30 minutes on a scale of 1 to 10, with 1 being very unhappy and 10 being very happy” (Csikszentmihalyi and Hunter, 2003; Bryson and Mackerron, 2016). Nearly all subjects reported being happy overall; only one reported a value of 5 (neither happy nor unhappy) and none responded with an answer less than 5. The average for this momentary happiness measure among all subjects was 7.86, with a standard deviation of 1.30. We see no statistically-significant differences in ex-post happiness between waiting conditions. This might be expected, though, since subjects were in the process of being paid when they were asked, and on average had asked for more compensation for more unfavorable waiting conditions. The average happiness in the four conditions was 7.83 for Nothing (n=6), 7.23 for Radio (n=13), 7.78 for Bluetooth (n=9) and 8.47 for Smartphone (n=15). We also asked the subjects who had actually waited : “if you could go back in time, do you wish your offer had not been accepted?”. None of them expressed regrets, suggesting that they had carefully considered their WTA offers.

4 Conclusions

We measured change in the utility of time spent waiting with and without the entertainment and productivity services of smartphones by directly eliciting WTA in an incentivized field experiment with student and non-student subjects. Three-quarters of respondents required differing levels of compensation under our four waiting conditions. On average, subjects required 24% more to wait with only access to the bluetooth services of their phone than with the full use of their phone, 48% more to wait with only an FM radio, and 79% more to wait in an empty, quiet room.

Our results have implications in several strands of literature. First, we believe our approach contributes to the literature on valuing internet services that are supported by advertising revenue and thus “free” to the consumer. Both [Brynjolfsson et al. \(2019\)](#) and [Allcott et al. \(2019\)](#) use incentivized mechanisms to elicit WTA for forgoing the services of Facebook for a certain period of time. Our approach bundles together the services smartphones provide (calls, internet browsing, using apps, streaming music or videos) and elicits the value subjects place on those services only for a very short amount of time. Future research could elicit WTA for longer periods of smartphone cessation to better estimate the total value of those services over the life of the smartphone. The small fraction of respondents in Figure 1 who asked for extremely high compensation to be without their phones may also be relevant to researchers investigating whether smartphone use is an “addiction” ([King et al., 2013](#); [Lee et al., 2016](#))

Second, our results are useful in assessing how the value of time spent traveling or waiting in public transportation, including air travel, may have changed over the past decade as smartphones have become ubiquitous. A number of researchers have suggested that travelers might view commuting times as less onerous with access to smartphones, laptops and tablets ([Kenyon and Lyons, 2007](#); [Lyons et al., 2016](#)), backed up by studies that use surveys or stated preference methods ([Frei et al., 2015](#); [Keseru and Macharis, 2018](#); [Zhou et al., 2018](#); [Varghese and Jana, 2018](#); [Kouwenhoven and de Jong, 2018](#)). Several revealed preference studies find the ability to multitask with smartphones or laptops increase the probability of travelers choosing public transport modes ([Pawlak et al., 2017](#); [Malokin et al., 2019](#); [Wyer and Wilson, 2017](#)).

Finally, given the continued predominance of single-occupancy vehicles among commuters in the United States, the value of reducing time spent travelling in private vehicles will remain a critical parameter in transportation planning. Our results suggest that this value of travel time savings may have decreased by approximately 12% since the advent of bluetooth-connected phones (using the “radio” condition as the base, subjects asked for 12% less compensation to wait in the bluetooth condition). Despite the accident and legal risks, however, many drivers do use the full set of features from their phones when driving. This suggests that our experiment, with its strict enforcement of phone access, may

underestimate the decline in the value of travel time savings. As vehicles gain increased autonomy this will free passengers to use their travel time in the same way that public transit or taxi riders would.

On one hand, this would imply that the value of travel time savings attributable to roadway investments will be smaller. Our results imply the value of reducing time spent traveling in a fully autonomous vehicle (FAV) could be an additional 12% smaller than saving time driving a conventional car with a bluetooth-connected phone (24% less than driving in a car with only an FM radio). Other research on fully-autonomous vehicles suggest that they will increase the productive use of time and decrease the disutility of travel. Survey-based studies find that drivers say they would use time traveling in FAVs productively or on leisure activities (see [Wadud and Huda \(2019\)](#)). Using a repeated stated preference discrete choice experiment, [Steck et al. \(2018\)](#) finds that FAVs decrease the value of travel time savings by 31%. Yet another conceptually similar stated preference study suggests that respondents value time in a FAV with an “office interior” 26% lower than time spent in a conventional car ([de Almeida Correia et al., 2019](#)). Using a combination of stated and revealed preference methods, [Kolarova et al. \(2018\)](#) find that the VOT for automated driving is lower than that of conventional cars. [Rashidi et al. \(2020\)](#), however, suggest that the VOT for automated vehicles (AV) may remain unchanged or even increase if, for example, FAVs do not provide a comfortable ride that facilitates multitasking or if riders do not trust their safety ([Yap et al., 2016](#)).

On the other hand, although our results imply a decrease in the value of travel time savings for investments, they also point to the private benefits of research and development in FAVs. Given the amount of time most Americans spend commuting, the welfare gains from this increased utility of travel time in FAVs is substantial.

References

Abrantes, Pedro A.L. and Mark R. Wardman, “Meta-analysis of UK values of travel time: An update,” *Transportation Research Part A: Policy and Practice*, 2011, 45 (1), 1 – 17.

- Aguiar, Mark, Erik Hurst, and Loukas Karabarbounis**, “Recent Developments in the Economics of Time Use,” *Annual Review of Economics*, 2012, 4 (1), 373–397.
- Allcott, Hunt, Luca Braghieri, Sarah Eichmeyer, Matthew Gentzkow, Nancy Baym, Moira Burke, Annie Franco, Alex Leavitt, and Todd Rogers**, “The Welfare Effects of Social Media,” 2019, pp. 1–114.
- Baxter, Jennifer, Lisa A. Robinson, and James K. Hammitt**, “Valuing Time in U.S. Department of Health and Human Services Regulatory Impact Analyses : Conceptual Framework and Best Practices,” Technical Report June, Industrial Economics 2017.
- Becker, Gary**, “A Theory of the Allocation of Time,” *The Economic Journal*, 1965, 75, 493–517.
- Berger, Roger, Heiko Rauhut, Sandra Prade, and Dirk Helbing**, “Bargaining over waiting time in ultimatum game experiments,” *Social Science Research*, 2012, 41 (2), 372–379.
- Boardman, Anthony, David H Greenberg, Aidan R Vining, and David L Weimer**, *Cost-benefit analysis: concepts and practices*, 5th ed., Upper Saddle River, NJ: Prentice Hall, 2018.
- Bohm, Peter, Johan Lindn, and Joakin Sonnegrđ**, “Eliciting Reservation Prices: Becker-DeGroot-Marschak Mechanisms vs. Markets,” *The Economic Journal*, 1997, 107 (443), 1079–1089.
- Brynjolfsson, Erik, Avinash Collis, and Felix Eggers**, “Using massive online choice experiments to measure changes in well-being,” *Proceedings of the National Academy of Sciences*, 2019, p. 201815663.
- Bryson, Alex and George Mackerron**, “Are You Happy While You Work?,” *Economic Journal*, 2016, 127 (202647), 106–125.
- Cason, Timothy N. and Charles R. Plott**, “Misconceptions and Game Form Recognition: Challenges to Theories of Revealed Preference and Framing,” *Journal of Political Economy*, 2014, 122 (6), 1235–1270.
- Cesario, Frank J**, “The value of time in recreation benefit studies,” *Land Economics*, 1976, 52 (1), 32–41.
- Csikszentmihalyi, Mihaly and Jeremy Hunter**, “Happiness in Everyday Life : the Uses of Experience Sampling,” *Journal of Happiness Studies*, 2003, 4 (January), 185–199.
- de Almeida Correia, Gonalo Homem, Erwin Loeff, Sander van Cranenburgh, Maaïke Snelder, and Bart van Arem**, “On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey,” *Transportation Research Part A: Policy and Practice*, 2019, 119, 359 – 382.
- DeSerpa, A.C.**, “A Theory of the Economics of Time,” *The Economic Journal*, 1971, 81 (324), 828–846.

- Ettema, Dick and Laura Verschuren**, “Multitasking and Value of Travel Time Savings,” *Transportation Research Record*, 2007, 2010 (1), 19–25.
- Fagnant, Daniel J. and Kara Kockelman**, “Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations,” *Transportation Research Part A: Policy and Practice*, 2015, 77, 167 – 181.
- Fezzi, Carlo, Ian J. Bateman, and Silvia Ferrini**, “Using revealed preferences to estimate the Value of Travel Time to recreation sites,” *Journal of Environmental Economics and Management*, jan 2014, 67 (1), 58–70.
- Frei, Charlotte, Hani S. Mahmassani, and Andreas Frei**, “Making time count: Traveler activity engagement on urban transit,” *Transportation Research Part A: Policy and Practice*, 2015, 76, 58–70.
- Hensher, D. A.**, “Measurement of the valuation of travel time savings,” *Journal of Transport Economics and Policy*, 2001, 35 (1), 71–98.
- Hensher, David A, Frank Milthorpe, Nariida Smith, and Peter Barnard**, “Urban Tolloed Roads and the Value of Travel Time Savings,” *Economic Record*, 1990, 66 (2), 146–156.
- Hong, Jinhyun, David Phillip McArthur, and Mark Livingston**, “Can accessing the internet while travelling encourage commuters to use public transport regardless of their attitude,” *Sustainability*, 2019, 11 (3281).
- Jeuland, Marc, Marcelino Lucas, John Clemens, and Dale Whittington**, “Estimating the private benefits of vaccination against cholera in Beira, Mozambique: A travel cost approach,” *Journal of Development Economics*, mar 2010, 91 (2), 310–322.
- Kecinski, Maik, Deborah Kerley Keisner, Kent D. Messer, and William D. Schulze**, “Measuring Stigma: The Behavioral Implications of Disgust,” *Environmental and Resource Economics*, 2018, 70 (1), 131–146.
- Kenyon, Susan and Glenn Lyons**, “Introducing multitasking to the study of travel and ICT: Examining its extent and assessing its potential importance,” *Transportation Research Part A: Policy and Practice*, 2007, 41 (2), 161 – 175. The Interaction Between ICT and Human Activity-Travel Behavior.
- Keseru, Imre and Cathy Macharis**, “Travel-based multitasking: review of the empirical evidence,” *Transport Reviews*, 2018, 38 (2), 162–183.
- King, A. L.S., A. M. Valença, A. C.O. Silva, T. Baczynski, M. R. Carvalho, and A. E. Nardi**, “Nomophobia: Dependency on virtual environments or social phobia?,” *Computers in Human Behavior*, 2013, 29 (1), 140–144.
- Kolarova, Viktoriya, Felix Steck, Rita Cyganski, and Stefan Trommer**, “Estimation of the value of time for automated driving using revealed and stated preference methods,” *Transportation Research Procedia*, 2018, 31, 35–46.
- Kouwenhoven, Marco and Gerard de Jong**, “Value of travel time as a function of comfort,” *Journal of Choice Modelling*, 2018, 28 (May), 97–107.

- Lee, Kyung Eun, Si-Heon Kim, Tae-Yang Ha, Young-Myong Yoo, Jai-Jun Han, Jae-Hyuk Jung, and Jae-Yeon Jang**, “Dependency on smartphone use and its association with anxiety in Korea,” *Public Health Reports*, 2016, 131 (3), 411–419.
- Lloyd-Smith, Patrick, Joshua K. Abbott, Wiktor Adamowicz, and Daniel Willard**, “Decoupling the Value of Leisure Time from Labor Market Returns in Travel Cost Models,” *Journal of the Association of Environmental and Resource Economists*, 2019, 6 (2), 215–242.
- , —, —, and —, “Intertemporal Substitution in Travel Cost Models with Seasonal Time Constraints,” *Land Economics*, 2020, 96 (3), 399–417.
- Lupi, Frank, Daniel J. Phaneuf, and Roger H. von Haefen**, “Best practices for implementing recreation demand models,” *Review of Environmental Economics and Policy*, 2020, 14 (2), 302–323.
- Lyons, Glenn and John Urry**, “Travel time use in the information age,” *Transportation Research Part A: Policy and Practice*, 2005, 39 (2), 257 – 276. Positive Utility of Travel.
- , **Juliet Jain, and Iain Weir**, “Changing times A decade of empirical insight into the experience of rail passengers in Great Britain,” *Journal of Transport Geography*, 2016, 57, 94–104.
- Mackie, P.J., S. Jara-Daz, and A.S. Fowkes**, “The value of travel time savings in evaluation,” *Transportation Research Part E: Logistics and Transportation Review*, 2001, 37 (2), 91 – 106. Advances in the Valuation of Travel Time Savings.
- Malokin, Aliaksandr, Giovanni Circella, and Patricia L. Mokhtarian**, “How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios,” *Transportation Research Part A: Policy and Practice*, 2019, 124 (December 2018), 82–114.
- Meeks, Robyn C.**, “Water Works,” *Journal of Human Resources*, 2017, 52 (4), 1119–1153.
- Mokhtarian, Patricia L.**, “The Times They Are A-Changin’: What Do the Expanding Uses of Travel Time Portend for Policy, Planning, and Life?,” *Transportation Research Record*, 2018, 2672 (47), 1–11.
- Noussair, Charles N. and Jan Stoop**, “Time as a medium of reward in three social preference experiments,” *Experimental Economics*, 2015, 18 (3), 442–456.
- Pawlak, Jacek, John W. Polak, and Aruna Sivakumar**, “A framework for joint modelling of activity choice, duration, and productivity while travelling,” *Transportation Research Part B: Methodological*, 2017, 106, 153–172.
- Rashidi, Taha Hossein, Travis Waller, and Kay Axhausen**, “Reduced value of time for autonomous vehicle users: Myth or reality?,” *Transport Policy*, 2020.
- Small, Kenneth A.**, “Valuation of travel time,” *Economics of Transportation*, 2012, 1 (1), 2 – 14.

- Steck, Felix, Viktoriya Kolarova, Francisco Bahamonde-Birke, Stefan Trommer, and Barbara Lenz**, “How Autonomous Driving May Affect the Value of Travel Time Savings for Commuting,” *Transportation Research Record*, 2018, 2672 (46), 11–20.
- Truong, Truong P. and David A. Hensher**, “Measurement of Travel Time Values and Opportunity Cost from a Discrete-Choice Model,” *The Economic Journal*, 1985, 95 (378), 438–451.
- Varghese, Varun and Arnab Jana**, “Impact of ICT on multitasking during travel and the value of travel time savings: Empirical evidences from Mumbai, India,” *Travel Behaviour and Society*, 2018, 12 (March), 11–22.
- Wadud, Zia and Fuad Yasin Huda**, “Fully automated vehicles: the use of travel time and its association with intention to use,” *Proceedings of the Institution of Civil Engineers –Transport*, 2019.
- Wardman, Mark and J. Nicolás Ibáñez**, “The congestion multiplier: Variations in motorists’ valuations of travel time with traffic conditions,” *Transportation Research Part A: Policy and Practice*, 2012, 46 (1), 213–225.
- Whittington, Dale and Joseph Cook**, “Valuing Changes in Time Use in Low- and Middle-Income Countries,” *Journal of Benefit-Cost Analysis*, 2019, 10, 51–72.
- Wyer, Joseph F and Wesley W. Wilson**, “Smartphones and Urban Transportation Mode Choice,” *SSRN Electronic Journal*, 2017, pp. 1–25.
- Yap, Menno D., Gonalo Correia, and Bart van Arem**, “Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips,” *Transportation Research Part A: Policy and Practice*, 2016, 94, 1 – 16.
- Zhou, Jiangping, Linchuan Yang, Jixiang Liu, and Chun Zhang**, “Beating long trips with a smartphone? A case study of Beijing residents,” *Cities*, 2018, 73 (November 2017), 36–43.

A1 Supplementary Appendix

Figure A1: Mean and standard deviation of the offers for each waiting program in the three rounds of BDM valuation of time.

