The value of time, with and without a smartphone

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Abstract

Smartphones can lower the disutility of waiting by increasing 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. We find little correlation between a subject’s wages and her offers, emphasizing the importance of heterogeneity in the value of time that is based on context rather than income.

Keywords: value of time, BDM; information technology

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1 Introduction

We focus in this paper on the disutility of time spent waiting, a ubiquitous feature of life. We wait at stores, restaurants, schools and clinics. Smartphones can make time pass more pleasantly by giving us access to music, entertainment, shopping, information and social connection. We also “wait” in vehicles stuck in traffic and on subways and buses. Commuters in the U.S. spent an average of 27.6 minutes traveling to work in 2019 (Burd et al. (2021)), and a variety of transportation researchers have noted that information technology improvements like smartphones can also decrease the disutility of time spent traveling by letting some types of employees accomplish work-related tasks (Lyons and Urry, 2005; Frei et al., 2015; Keseru and Macharis, 2018; Varghese and Jana, 2018; Hong et al., 2019; Wyer and Wilson, 2017; Zhou et al., 2018; Malokin et al., 2019). Other commuters who cannot do work-related tasks with phones or computers, however, may benefit from the ability to reduce the drudgery of the trip. Using a stated preference approach, Ettema and Verschuren (2007) found that commuters who listen to music while traveling, for example, have a smaller willingness to pay (WTP) to shorten commuting times. This may also be true for people who could use the time productively on their commute home but are tired after a long day and choose not to.

This has clear and important implications for the cost-benefit analysis of time-saving public investments in roadway improvements or public transportation. Several stated preference studies find that technology’s ability to make travel time more productive decreases willingness to pay for shorter travel times (Ettema and Verschuren, 2007; Kouwenhoven and de Jong, 2018; Steck et al., 2018; Yap et al., 2016). Malokin et al. (2019) use a revealed preference approach to model the choice of transportation mode in northern California, finding that the ability to use a laptop or tablet has a small but non-trivial influence on the share of commuters driving versus taking various types of public transportation. Mokhtarian (2018) discusses how information technology may have caused the valuation of travel time to change in recent decades with the advent of information technology, though there
is no consensus on the magnitude of this change. Mokhtarian (2018) also speculates how the advent of fully-automated vehicles may change the perceived disutility of travel times.

Our contribution is a direct and incentive-compatible revealed preference test of how the value of time spent waiting changes based on access to smartphone services. We use a Becker-DeGroot-Marschak (BDM) mechanism to elicit subjects’ required compensation for waiting for 30 minutes, alone in an empty room, under four different conditions (described in more detail below): 1) unrestricted smartphone use, 2) use only of Bluetooth features for calling or streaming music, 3) use of phone physically restricted but an FM radio provided, and 4) with neither FM radio nor phone. We chose the first three conditions in part to mimic how smartphones may have changed the disutility of time spent commuting in a single-occupant vehicle over the past two decades and how they might further change with adoption of fully automated vehicles. For each subject, we randomly selected one of the waiting conditions and randomly drew our researcher’s willingness-to-pay (WTP). If the WTP exceeded the subject’s bid, the subject actually waited and was compensated the randomly-drawn WTP. We recruited subjects from the local community who span a wide age range. Fifty-seven percent were non-students.

We find that one quarter of our eighty subjects did not distinguish between 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. We were surprised to find no difference in the relative utility of waiting without smartphone services among those over and under age 25, since the latter have essentially grown up in a world with smartphones.

Although our study was small and conducted in only one geographic location, we believe our estimate of the magnitude of the effect of smartphone services on the disutility of waiting time is credible and informative, and our basic design could be usefully replicated by other researchers. Our findings have implications for the literature on valuing time savings for both travelers using single-occupancy vehicles (including fully-automated vehicles), taxis, or public transportation in the context of cost-benefit analyses. Because
our experiment did not allow the use of laptops or tablets, however, our results may underestimate additional productivity benefits for commuters that might prefer to read on larger screens or type with keyboards. Nevertheless, if the disutility of long commutes is mitigated by access to smartphones, this would have implications for urban development patterns, allowing workers to locate further from job centers (Mokhtarian, 2018). A shift spurred by the COVID-19 to allow employees to work from home several days per week might amplify this movement away from congested central business districts (Ramani and Bloom, 2021), as would further development of automated vehicles (Steck et al., 2018). In addition to commuters, a reduction in the disutility of travel time since the advent of smartphones in 2007 may have lowered the “time price” of trips to recreation sites, a key parameter in the environmental literature on travel cost models (Lupi et al., 2020). Our results also speak to the literature on valuing unpriced internet services (Brynjolfsson et al., 2019; Allcott et al., 2020) and the possibility of internet “addiction” (King et al., 2013; Lee et al., 2016). Finally, echoing two other recent studies using stated preference methods (Czajkowski et al., 2019; Lloyd-Smith et al., 2019), we also find a low correlation between a subject’s wage rate and her offers to wait. This suggests that using the predominant analytical practice of valuing waiting or traveling time as a fixed fraction of income may be a mistake.

In the next section we briefly review the literature and conceptual framework on valuing time. We then describe our methods and subject recruitment in section 3 and empirical results in section 4. Section 5 mentions study limitations and discusses the implications of our findings in more detail.

2 Literature Review

Valuing changes in how people allocate their time is of central interest in several fields of economics, including transportation (Wardman, 2001), 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 cost-benefit 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) lists “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 a 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: older respondents, those in larger households, and the self-employed, demanded 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.

Research on fully-autonomous vehicles (FAVs) 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
3 Methods

We used the incentive-compatible Becker-DeGroot Marshak (BDM) mechanism 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 the small FM radio. This condition was intended to mimic the experience of a driver today accessing the hands-free smartphone features legally approved in most states. 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. This condition was intended to mimic the experience of a driver before the advent of mobile phones. 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 would increase across these conditions, with the corresponding willingness-to-accept (WTA) for each condition also increasing.

After eliciting WTA estimates for each of the four conditions, we then used a computer to randomly generate the experimenter’s 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 for the selected
waiting condition, 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 the subjects would
have actually waited for 30 minutes and their 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 final, 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 made a deliberate effort to recruit non-student subjects. We recruited using flyers
posted at businesses throughout the towns of Pullman (WA) and Moscow (ID) and on the
WSU campus and advertisements in the local newspaper (see Appendix Figures A2, A3).
We used the USPS Every Door Direct Mail service to send mailers to every address in the
two Pullman postal routes (of a total of 13) that we judged were most likely to have non-
student residents (see Appendix Figure A4). We also had a large local employer post the
ad to their internal listserv and we made oral announcements in large WSU classes. In all
materials, we emphasized that subjects would earn $15 for completing a 15-minute survey
but would have the option to stay for an additional 30 minutes and “earn an additional
amount of money negotiated by you and the researchers.” The experiments were conducted
between July and December 2019.

Before proceeding, we note several limitations of our methods. First, because of our
low response rate\(^1\), it is likely that we recruited subjects with a lower value of time than the overall population of the two towns. If our objective was to estimate VOTs, this selection bias would be a major concern. Our objective, however, was to measure the relative disutility of waiting under different conditions using variation within a subject’s answers, not the absolute values or the variation between subjects\(^2\). We attempted to counter this selection problem by offering a show-up fee that was relatively large ($15) relative to total earnings, though this may have then anchored subjects’ subsequent offers to wait\(^3\). Although this would be a major concern if our study was attempting to estimate the value of waiting time, we are again concerned only with relative comparisons: a high show-up fee may have anchored all offers upwards but should have left intact the relative compensation required for different treatments. Because we were sensitive to detaining subjects even longer than promised, we did not ask exit questions about what subjects who waited in the Smartphone or Bluetooth conditions did during their waits, so it is unfortunately not possible for us to separate how much of the premium for these two conditions was due to increased productivity as opposed to simple entertainment. Finally, we did not have statistical power to vary the amount of time spent waiting under the four conditions. We chose 30 minutes because it seemed a reasonable amount of time to ask when recruiting subjects. It is also close to the average one-way commuting time in the US in 2019 of 27.6 minutes (Burd et al. (2021)).

4 Results

We recruited 82 subjects in total. This was fewer subjects than specified in our registered pre-analysis plan. We decided to proceed (at the cost of lower explanatory power)
because exhaustive recruiting efforts were yielding smaller and smaller subject contacts and because data collection had already been ongoing for 6 months. There were no other deviations from our pre-registration plan. 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. The majority of our subjects were non-students; forty-three percent of our 80 subjects were WSU students. Nearly three quarters 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 median annual earnings of salaried workers was $37,500 (salaries were asked in ranges; average=$50,657). This is somewhat lower than the 2019 American Community Survey 5-year estimate, which found that the median income of full-time, year-round workers in Pullman WA was $44,507. We did not ask questions about work expectations for salaried workers, but assuming 40 hours per week and 52 weeks per year, the average implied hourly wage rate is $24.35 (median $18.03).

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 in Table 1. (Because of this, we need an assumption for retirees and currently unemployed subjects: we assume $12 per hour, the 2019 minimum wage in Washington State.) Our primary 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 the level of offers or differences across subjects.

The majority of subjects perceived differences in the disutility of waiting under the four different conditions and required different compensation, though one-quarter of subjects asked for the same compensation for all four conditions in the final, real round. We did not explicitly test for whether subjects misunderstood the incentives of the BDM tasks (Cason and Plott, 2014) with comprehension checks like those used recently in Berry et al.
Despite our efforts to explain the procedure with simple language and two practice rounds, it is possible that subjects who reported the same WTA for all four waiting conditions were confused by the experiment. They may also have understood the BDM mechanism but viewed their WTA offers in a worker-employer context: after subjects agreed to an employment contract lasting 30 minutes, we as “employers” had discretion over how they spent that time. Based on informal conversations with participants, we think it is plausible that subjects did not perceive a difference between the four conditions. This might occur if they planned to just sit quietly in the room and not take advantage of access to the phone or radio, even if allowed. We 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).

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).

4 Burchardi et al. (2021) found little evidence of subject miscomprehension in a study in rural Uganda.
Table 1: Monetary compensation required to wait for 30 minutes under four conditions

<table>
<thead>
<tr>
<th>Offers</th>
<th>Test of differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dollars</td>
</tr>
<tr>
<td></td>
<td>Mean (se)</td>
</tr>
<tr>
<td>Nothing</td>
<td>17.91 (1.49)</td>
</tr>
<tr>
<td>Radio</td>
<td>15.63 (1.42)</td>
</tr>
<tr>
<td>Bluetooth</td>
<td>13.21 (0.97)</td>
</tr>
<tr>
<td>Smartphone</td>
<td>11.18 (0.82)</td>
</tr>
<tr>
<td>N =</td>
<td>80</td>
</tr>
</tbody>
</table>

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 us 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 sym-
bols lie on top of each other). The figure is partitioned by age. We hypothesized that
subjects who have had smartphones for nearly all of their lives would demand a higher
compensation to wait without their phones (higher ratios in Figure 1) than older subjects.
Since the iPhone was released in 2007, we used the age of 25 as our cutoff. This pattern is
not apparent in the figure, however, and Wilcoxon rank-sum tests showed no statistical dif-
ference 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. A possible explanation for
the lack of difference in offers by age is hedonic adaptation, or the idea that people adapt
to positive (and negative) shocks to their well-being within a relatively short period of time
and return to a baseline level of well-being (Diener et al., 2006). Hence, it may not matter
whether one “grew up” with a smartphone: nearly all of our subjects would have been
using smartphones long enough to grow accustomed to them.

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 pairwise 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).
Two other recent studies also find weak relationships using stated preference approaches.
Lloyd-Smith et al. (2019) finds a correlation coefficient between the elicited value of travel
time savings and the hourly wage rate of 0.58; the correlation in Czajkowski et al. (2019)
is only 0.04.

Model 3 explores interactions between demographics and differences among a sub-
ject’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 a 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 1.48 can be interpreted to mean that a male subject who was over age 25, unemployed or retired, and not a student required 47% higher compensation, on average, to wait in the Nothing condition compared to the Smartphone condition. He required 25% more to wait with the Radio condition (calculated as 1.48 minus 0.23), and 10% 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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4) Percent of offer for Smartphone treatment</th>
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<tbody>
<tr>
<td></td>
<td>Offer (dollars)</td>
<td>Offer (dollars)</td>
<td>Offer (dollars)</td>
<td></td>
</tr>
<tr>
<td>Nothing</td>
<td>6.74***</td>
<td>6.74***</td>
<td>4.87**</td>
<td></td>
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<tr>
<td></td>
<td>(6.27)</td>
<td>(6.21)</td>
<td>(2.12)</td>
<td></td>
</tr>
<tr>
<td>Radio</td>
<td>4.46***</td>
<td>4.46***</td>
<td>2.84</td>
<td>-0.23**</td>
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<td></td>
<td>(4.49)</td>
<td>(4.45)</td>
<td>(1.42)</td>
<td>(-2.60)</td>
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<tr>
<td>Bluetooth</td>
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<td>2.04***</td>
<td>0.76</td>
<td>-0.38***</td>
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<td>(4.66)</td>
<td>(4.61)</td>
<td>(0.83)</td>
<td>(-3.27)</td>
</tr>
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<td>Under25</td>
<td>-4.93*</td>
<td>-3.62</td>
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<td></td>
<td>(-1.88)</td>
<td>(-1.41)</td>
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<tr>
<td>Female</td>
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<td></td>
<td>(-0.37)</td>
<td>(-1.17)</td>
<td>(1.59)</td>
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<td>-2.06</td>
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<td></td>
<td>(-0.74)</td>
<td>(-0.73)</td>
<td>(0.65)</td>
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<td>Salaried</td>
<td>0.22</td>
<td>0.22</td>
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<td></td>
<td>(0.09)</td>
<td>(0.09)</td>
<td>(0.22)</td>
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<tr>
<td>Hourly</td>
<td>0.42</td>
<td>0.42</td>
<td>0.053</td>
<td></td>
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<tr>
<td></td>
<td>(0.19)</td>
<td>(0.19)</td>
<td>(0.26)</td>
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<tr>
<td>Hourly wage rate</td>
<td>0.023</td>
<td>-0.018</td>
<td>0.0015</td>
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<tr>
<td></td>
<td>(0.23)</td>
<td>(-0.36)</td>
<td>(0.22)</td>
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</tr>
<tr>
<td>Radio X Under 25</td>
<td>-1.83</td>
<td>0.014</td>
<td>0.12</td>
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</tr>
<tr>
<td></td>
<td>(-1.41)</td>
<td>(0.12)</td>
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<tr>
<td>Radio X Wage Rate</td>
<td>0.059</td>
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<tr>
<td></td>
<td>(0.53)</td>
<td>(-0.26)</td>
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<td></td>
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<tr>
<td>Radio X Female</td>
<td>1.74</td>
<td>-0.10</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.93)</td>
<td>(-0.96)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nothing X Under 25</td>
<td>-2.40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.48)</td>
<td></td>
<td></td>
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<tr>
<td>Nothing X Wage Rate</td>
<td>0.075</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.59)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nothing X Female</td>
<td>1.98</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.96)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Bluetooth X Under 25</td>
<td>-1.01</td>
<td>-0.020</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.35)</td>
<td>(-0.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bluetooth X Wage Rate</td>
<td>0.029</td>
<td>-0.0012</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.69)</td>
<td>(-0.26)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bluetooth X Female</td>
<td>1.61*</td>
<td>-0.19</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.93)</td>
<td>(-1.19)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>11.2***</td>
<td>13.7***</td>
<td>14.9***</td>
<td>1.48***</td>
</tr>
<tr>
<td></td>
<td>(13.49)</td>
<td>(5.21)</td>
<td>(7.92)</td>
<td>(7.10)</td>
</tr>
<tr>
<td>Observations</td>
<td>320</td>
<td>320</td>
<td>320</td>
<td>240</td>
</tr>
</tbody>
</table>

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.
Finally, we asked 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. 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 see no statistically-significant differences in ex-post happiness between waiting conditions. These results contrast somewhat with Wilson et al. (2014), who found in 11 lab experiments that subjects were unhappy when asked to wait in an empty room for 6 to 15 minutes, similar to our Nothing condition. Two thirds of their male subjects disliked waiting alone with their thoughts so much that, to pass the time, they voluntarily self-administered one or more electric shocks that they had previously experienced and expressed a monetary WTP to avoid (25% of female subjects shocked themselves). Our result might be expected, though, since subjects were in the process of being paid when they were asked, and on average they had asked for more compensation for more unfavorable waiting conditions. 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.

5 Conclusions

We measured the change in the disutility 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.

Some of the study’s limitations noted above point to possible avenues for future research. First, because our study was small and in a specific geographic location, it would be useful to test whether our pattern of results holds in other settings and populations. Second, we chose 30 minutes as the default waiting period, though it is certainly possible that the relative disutility of waiting under our four conditions would not scale linearly if, for example, the time spent waiting increased to 180 minutes or decreased to 15 minutes. We are unaware of existing evidence that speaks to this relationship; future research could address this. Furthermore, one might expect our results to change based on whether the waiting environment was noisy rather than quiet. Given that our recruitment materials prompted subjects to anticipate the waiting period, it would also be useful to explore how the disutility of waiting with a smartphone changes when the wait is unexpected.

Although our results speak to the literature on valuing internet services and “addiction”, they are more likely to be policy-relevant in the transportation sector. Given the continued predominance of single-occupancy vehicles among travelers in the United States, the value of reducing time spent traveling in private vehicles will remain a critical parameter in transportation planning and recreation demand studies. 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 riders on public transit or in taxis would. Our results imply the value of reducing time spent travel-

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\[5\] Both Brynjolfsson et al. (2019) and Allcott et al. (2020) 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).
ing 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).

On one hand, our results imply that the value of travel time savings attributable to road-
way investments will be smaller, although a recent set of natural experiments using data
from the Lyft rideshare service suggests the US government should revise their existing
VOT parameters upwards (Goldszmidt et al., 2020). On the other hand, they point to the
private benefits of research and development in vehicle automation. Given the amount of
time most Americans spend commuting, the aggregate welfare gains from this increased
utility of travel time in FAVs are substantial.

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Figure A1: Mean and standard deviation of the offers for each waiting program in the three rounds of BDM valuation of time.
Figure A2: Recruitment materials: Flyer posted on WSU Campus and at businesses throughout Pullman and Moscow

![Flyer Image]

- Participate in research study on WSU Pullman campus about the value of time
- After completing a 15-minute survey, you have the option to stay for an additional 30 minutes and earn an additional amount of money negotiated by you and the researchers.
- Evenings and weekends possible; ask about parking reimbursement
- Particularly interested in people ages 25-60
- Must speak English

For more information or to schedule an appointment, email [redacted] or scan the QR

This research has been certified exempt for human subjects by WSU's Institutional Review Board. To discuss any concerns about the study, contact [redacted].

Figure A3: Recruitment materials: Advertisement (run six times) in The Moscow Pullman Daily News

![Advertisement Image]

Participate in a research study with the School of Economic Sciences at WSU!

[redacted] is conducting an experiment to determine how people value their time under different conditions. The experiment has two parts. The first part, which will last 15 minutes, asks you to answer a short survey and earn $15. If you stay for the second part, which will last an additional 30 minutes, you can earn an additional amount of money that will be determined by you and the researchers. If you would like more information or want to enter the study, send an email to: [redacted]

This research has been certified exempt for human subjects by WSU's Institutional Review Board. To discuss any concerns about the study, please contact [redacted].
Figure A4: Recruitment materials: Mailer (front and back) sent to approx. 1400 addresses in Pullman WA