Back to Edgeworth?

Estimating the Value of Time Using Hedonic Experiences

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Abstract

Following early economist Francis Y. Edgeworth's proposal to measure people's hedonic experiences as they go about their daily lives, we use a smartphone app that randomly asked a panel of $30,936$ UK residents ($N = 2,235,733$) over the course of eight years about their momentary feelings and activities, to derive a causal parameter for the value of time (VOT), a key input into cost-benefit analyses. Exploiting the randomisation of messages for identification, we arrive at a VOT of £8.3 ($11.2) per hour, considerably smaller than estimates currently used by UK Government. While our parameter is more generalisable than previous ones, applying across a broad range of activities and their contexts, our unique data and method also allow us to derive activity-specific estimates. These closely resemble those from studies using revealed preferences, suggesting that using hedonic experiences to value intangibles may lead to very similar results as observed behaviour. We are the first to estimate the VOT (or indeed any intangible) using hedonic experiences in real-time, which has the potential to value other intangibles too.

Key Words: Value of Time, Experience-Sampling, Valuation, Cost-Benefit Analysis, Waiting, Commuting

JEL Codes: R4, D61, I31

1 Introduction

Time matters a great deal to people. How individuals spend their time determines to a large extent how satisfied they are with their lives overall (Smeets et al., 2019), and in particular, how happy they are on a moment-to-moment basis (Kahneman et al., 2004; White and Dolan, 2009; Bryson and MacKerron, 2017). The significance of time for people's lives has led some to argue that time is the ultimate scarce resource. Following this line of argument, the term *time poverty* has recently gained traction (Giurge et al., 2020), to describe those who have plenty in material wealth but are poor in time, with an active research agenda to reduce it (Hershfield et al., 2016; Whillans et al., 2016, 2017, 2019).

To the extent that markets fail to provide the means for people to optimally allocate their time (e.g. through investments into time-saving infrastructure such as roads or railways), there is an economic rationale for public policy to intervene. Indeed, it is estimated that the average UK road user loses about 115 hours to congestion every year, albeit with major disparities between areas (149 hours in London, compared to 98 in Edinburgh or 75 in Hull). In the US, the loss is estimated to be about 100 hours (149 hours in Boston, 103 in Los Angeles, and 82 in Atlanta) (INRIX, 2019b,a). These figures point towards a huge potential for investments. But how shall economists value time and associated time savings, key inputs into cost-benefit analyses?

Time has received rather little attention in economics, relative to other concepts. Yet, there exists an established literature that attempts to put a price tag on time, dating back to classic time allocation studies such as Becker (1965), in which market goods and time are inputs into household production and a time budget is split between labour and leisure such that leisure time is optimally valued at the prevailing wage rate; Johnson (1966), Oort (1969), and Evans (1972), who develop the idea that working hours themselves cause disutility, so that leisure time is valued at *more* than the wage rate; or DeSerpa (1971), who introduces constraints in time allocation. Today, most empirical studies attempting to estimate the *value of time (VOT)* look at reductions in search, travel, or waiting time. They can be broadly categorised into two streams.

The first, which relies on *stated preferences* and includes mostly discrete choice experiments or contingent valuation studies, directly asks people how much they would be willing to pay for, for example, a hypothetical reduction in travel time due to a new toll (Calfee and Winston, 1998). The second relies on *revealed preferences* and consists of either observational studies, e.g. observing road choices with different travel times and tolls, or choices of potential ride shares with different waiting times and prices (Lam and Small, 2001; Small et al., 2005; Fezzi et al., 2014; Buchholz et al., 2020); quasi-natural experiments, e.g. studies that exploit exogenous variations in gas prices across areas and record the willingness to queue longer for a lower price, or that look at speeding (Deacon and Sonstelie, 1985; Wolff, 2014); or natural field experiments, e.g. studies that experimentally manipulate bundles of waiting times and prices offered to users of ride-sharing apps (Goldszmidt et al., 2020). While stated-preference studies typically estimate the VOT to be less than 25% of the mean wage rate, observed behaviour often reveals much higher values, typically in excess of 75%.[1]

At their core, studies relying on revealed preferences go back to the early economist Irving Fisher (1867-1947) and his concept of "backwards-inducing" people's optimal choices from their observed behaviour (cf. Fisher, 1892). Overcoming issues of stated preferences such as attitude expression, social desirability, or strategic answers, they are often considered the gold standard to value intangibles, including time.

Yet, underlying these studies lies the fundamental assumption that people act rationally and with perfect foresight: once they are – either by chance or by experimental manipulation – presented with different choices, for example between different waiting times and payments to reduce them, they choose the option that maximises their welfare, thereby revealing their true preference for time. While this assumption has desirable analytical properties, it also brings with it three fundamental problems.

First, we know from research on heuristics and biases that how choices are presented matters a great deal for choice behaviour, e.g. whether choices are presented in a gain or a loss frame, like "time saved" or "time lost" (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981; Kahneman and Tversky, 1984), which is particularly problematic for stated but may befall revealed preferences too. Likewise, well-documented

[1] Appendix Table **??** shows estimates from the literature by valuation method.

cognitive biases in intertemporal choice such as present bias are likely to also systematically bias how individuals value time itself (Thaler, 1981; Loewenstein and Prelec, 1992; Laibson, 1997). Second, what exactly constitutes search, travel, or waiting time may be subjective. Related, the concept of *subjective time perception* suggests that the perceived passage of time is not the same as chronological time (Read, 2001; Prelec, 2004; Bradford et al., 2019), and what matters is the context in which that passage is experienced, e.g. time spent waiting with a friend or a loved one may be experienced quite differently than time spent waiting alone, or may not be experienced as waiting at all (Kim and Zauberman, 2013; Xu et al., 2020). Third, studies relying on revealed preferences implicitly assume that individuals are capable of *ex-ante* predicting the welfare consequences of different choices at the point of decision-making.

Yet, economic agents may not be perfectly informed about their own preferences and what influences their welfare under different conditions. In fact, there is a large body of evidence on prediction errors in economics (Loewenstein et al., 2003; Loewenstein and Adler, 2005) and on failures in affective forecasting in psychology (Wilson and Gilbert, 2003), showing that individuals make large, systematic errors when predicting the welfare consequences of particular choices and events (cf. Odermatt and Stutzer, 2019).

We propose an alternative method – *experiential valuation* based on experience-sampling – to estimate the VOT. In particular, our method does not require individuals to *ex-ante* predict the welfare consequences of different choices at the point of decision-making but, instead, looks at their hedonic experiences once they have made their decisions.[2] Or, put differently, it does not rely on how individuals *think* what the welfare consequences of different choices will be but, instead, relies on how they actually *feel* while experiencing them.

The idea behind experience-sampling goes back to the early economist Francis Y. Edgeworth (1845-1926), a contemporary of Fisher, who, in his treatise *Mathematical Psychics* (1881), argued that new technical developments would make it possible to develop a *hedonimeter*, which would allow economists to directly measure utility on a physiological basis. [3] Already acknowledging that individuals are prone

[2]Our argument mirrors that by (Kahneman et al., 1997) who make a distinction between *decision* and *experienced utility*.

[3]Fisher, like Edgeworth, believed in the importance of utility measurement. However, he did not trust direct

to making systematic errors, Edgeworth envisioned the hedonimeter as a “psychophysical machine, continually registering the height of pleasure experienced by an individual, exactly according to the verdict of consciousness, or rather diverging therefrom according to a law of errors” (Edgeworth, 1881, p. 101).

Our method to estimate the VOT builds on Edgeworth’s hedonimeter, although with three key differences: while Edgeworth’s vision was to directly measure utility, our measure of hedonic experiences does not have to be equal to utility. For our purpose, it is enough that individuals sufficiently care about their experiences and that these matter for their choice behaviour. Fortunately, for our measure – whether an individual feels happy – there is now a sufficiently large evidence base using choice experiments and vignette studies suggesting that individuals care a great deal about how happy they are, in general and on a moment-to-moment basis (cf. Benjamin et al., 2012; Adler et al., 2017). Edgeworth himself suggested ‘happiness’ for his hedonimeter, being fully aware of its imperfections.[4] The other differences are more practical in nature: we collect data using self-reports, in discrete rather than continuous time.

Our *hedonimeter light* is a smartphone app that sampled the hedonic experiences of $30,936$ UK residents ($N = 2,235,733$) longitudinally as they went about their daily lives during the years 2010 to 2017. Our app messaged these individuals at *random* points in time and asked them *(i)* how happy they felt at that particular point in time, *(ii)* where they currently were, *(iii)* who they were with, and *(vi)* what they were currently doing. Whilst replying, their location was recorded using GPS.

We use these rich panel data to estimate the VOT. In particular, we closely follow the literature by estimating the willingness-to-pay to reduce *waiting time*. Our method has three steps: exploiting the randomisation of messages by the app, we first estimate the causal effect of *waiting or queueing* on respondents’ happiness when randomly messaged. We then calculate the marginal rate of substitution between waiting

measurement (i.e. via human perceptions) and thus favoured indirect measurement (i.e. via observed behaviour). He argued that a “physicist would certainly err who defined the unit of force as the minimum sensible of muscular sensation” (Fisher, 1892, p. VI). Of course, this begs the question as to how much observed behaviour itself can be trusted if behaviour follows from perception.

[4]Edgeworth, like many of his contemporaries, was rather pragmatic. For example, on cardinality and interpersonal comparability, he argued that the “greater uncertainty of hedonimetry in the case of others’ pleasures may be compensated by the greater number of measurements, a wider average; just as, according to the theory of probabilities, greater accuracy may be attained by more numerous observations with a less perfect instrument” (Edgeworth, 1881, p. 102).

and income, to obtain the income equivalent respondents would be willing to pay in order to avoid waiting. Finally, we duration-adjust that willingness-to-pay to exactly one hour, exploiting data on the share of responses respondents report to be waiting amongst all activities. Our regressions look at within-individual variation when randomly messaged, controlling for 41 other activities respondents may be simultaneously engaged in. We also control for where they currently are (i.e. at home, at work, or elsewhere; indoors, outdoors, or in a vehicle); who they are with (i.e. partners, children, other family members, colleagues or classmates, friends, other people they know, or alone or with strangers); meteorological conditions (i.e. air temperature, wind speed, precipitation, cloud cover and sunshine, and daylight); and region and time (i.e. Middle Layer Super Output Area, holiday-season, hour-of-day, day-of-week, month and year) fixed effects.

We obtain an average willingness-to-pay to reduce one hour of waiting time – our preferred estimate of the VOT – of about £8.3 ($11.2).[5] While our estimate is more generalisable than previous ones, applying across a broad range of activities and their contexts rather than looking at a single domain, our unique data and method also allow us to derive activity-specific estimates. For a reduction in waiting time during *travelling or commuting*, for example, individuals would be willing to pay, on average, about £13.0 ($17.7) per hour. This is similar to the estimate by Goldszmidt et al. (2020), who use natural field experiments amongst users of the Lyft ride-sharing app (about $19). However, it is considerably smaller than estimates currently used by UK Government.[6] Compared to hourly wages in the UK in 2021, our generalised estimate of the VOT is about 59% of the median wage, which is £14.1 ($19.2) (Office for National Statistics, 2021). Using this estimate, and noting that respondents in our study spend, on average, 21 minutes per day waiting, either by itself or while doing other things, we calculate that the total monetised hedonic welfare loss to the UK from waiting across *all* activities and contexts is about £65.7 billion ($89.1 billion) per year, or about 3.4% of GDP.

When estimating the VOT via a reduction in waiting time, we estimate it via a reduction in a bad.

[5] All $ figures are converted from £using an exchange rate of 1 : 1.36, current at January 23, 2022.

[6] The UK Department for Transport (DfT) values one hour of working time at about £38.5 ($52.4). One hour of leisure time is valued lower, though, at about £19.9 ($27.1) for leisure time spent commuting and £9.1 ($12.4) for leisure time spent doing other things (DfT, 2021a,b).

However, freeing up one additional hour of time not only reduces the displeasure from waiting one hour but also allows people to put that hour to alternative, ideally good, use, by spending it on relatively more pleasurable activities instead. Our method gives us the unique opportunity to move beyond existing studies, which lack data on what people are doing beyond a narrow domain, by estimating a novel counterfactual: the *value of opportunity time (VOOT)*, i.e. the value of the additional hour of free time that is obtained from reducing one hour of waiting time and that can be re-allocated to other activities, holding selection into activities constant. Applying the same methodology as for the VOT, we obtain a $VOOT$ of about £9.1 ($12.4) per hour. The $VOOT$ provides a natural upper bound to the monetary value of one hour of time, which lies within the interval $[VOT; VOOT]$, i.e. £$[8.3; 9.1]$ (\$$[11.2; 12.4]$).

Our method has several key innovations over existing studies. First, it does not rely on choice architecture and how choices are presented to individuals. Second, it allows individuals to judge for themselves what constitutes waiting time. In line with the importance of *subjective time perception*, subjectivity is an important asset here. Third, it allows us to derive an estimate of the VOT that is more generalisable than previous ones, applying across a broad range of activities and their contexts rather than looking at a single domain, while being flexible enough to provide activity-specific estimates. Our sample is also broader, covering a wider range of individuals than studies relying on small-scale experiments or specific subgroups like ride-share users. Finally, and most importantly, our approach does not assume that individuals act rationally and with perfect foresight, capable of *ex-ante* predicting the welfare consequences of their choices at the point of decision-making.

To the best of our knowledge, our paper is the first to document how people actually feel when *waiting or queueing*, exploiting the only experience-sampling study that includes this variable. Perhaps unsurprisingly, respondents experience it as unpleasant. More interesting, however, is just how unpleasant it is: amongst all 42 activities recorded, *waiting or queueing* ranks third to bottom, outranked only by *being sick in bed* and *care or help for adults*. Interestingly, this experience seems to be universal: we find little evidence of heterogeneity by different demographic (i.e. age, health status, or having children) or socio-economic characteristics (i.e. income). Our paper is the first to exploit hedonic experiences in real-time to estimate the VOT (or indeed any intangible). To differentiate our method from that using accounts of self-reported life satisfaction to value intangibles – which is often referred to as *experienced preference valuation* (Kahneman and Sugden, 2005; Welsch and Ferreira, 2014) – we refer to it as *experiential valuation*.

Our paper contributes to the literature in transportation and infrastructure economics that attempts to value time, which mostly looks at reductions in search, travel, or waiting time and which, so far, relies exclusively on stated or revealed preferences (Deacon and Sonstelie, 1985; Calfee and Winston, 1998; Lam and Small, 2001; Small et al., 2005; Fezzi et al., 2014; Wolff, 2014; Buchholz et al., 2020; Goldszmidt et al., 2020). Our paper adds an alternative method. It also contributes to the literature, mostly in public and environmental economics, that uses accounts of self-reported life satisfaction for non-market valuation (van Praag and Baarsma, 2005; Luechinger, 2009; Luechinger and Raschky, 2009; Maddison and Rehdanz, 2011; Levinson, 2012; Krekel and Zerrahn, 2017; von Möllendorff and Welsch, 2017; Dolan et al., 2019, 2021). Our paper shows how hedonic experiences in real-time can be used as an alternative.

2 Data and Methods

2.1 Data

At the core of our study are individual-level panel data which we collected via a smartphone app called *Mappiness*.[7] The app was developed for iPhone and was distributed via Apple's App Store from 2010 onwards at no charge. It gained prominence and popularity in the UK thanks to broad coverage in traditional and social media. For example, the app was highlighted in the *Featured* section of Apple's App Store for more than two weeks after its launch, and it has heavily featured on social networking sites like Facebook and Twitter as well as on television (i.e. the BBC), radio, and in the specialist and mainstream press. As a result, a much broader range of individuals self-selected into using the app compared to other, often much

[7] http://www.mappiness.org.uk

smaller-scale experience-sampling studies. Participation was incentivised by providing participants with regular, personalised feedback on their happiness in different contexts. Participants could take part in the study for as long as they wished. The median days of participation were 52, with mean 143 and standard deviation 467. Appendix Figures A1 to A4 show screenshots of the app.

After downloading the app, participants (who had to be above 18 years of age) first had to give their informed consent to take part in the study. Then, they were forwarded to a short intake survey which was integrated into the app and asked to provide basic demographic and socio-economic information, including their age, gender, marital status, health, employment status, and overall satisfaction with life, as well as certain household characteristics (i.e. the number of adults and children living in the household and household income). The survey was completed only once, before any data on hedonic experiences were collected so as to not prime respondents when these were asked about their momentary feelings. Table 1A shows summary statistics of our intake survey.

Table 1A about here

After completing the intake survey, the app started operating. In particular, participants were messaged (pinged) at *random* times during their days (the default being twice a day between 8am and 10pm) and asked to complete a short experience-sampling survey.[8] This randomly recurring survey asked participants to report on, in the following order to avoid priming: *(i)* how *happy* they felt at that particular point in time (i.e. hedonic experiences); *(ii)* where they currently were (i.e. place and location, single choice, including *at home*, *at work*, or *elsewhere*, as well as *indoors*, *outdoors*, or *in a vehicle*); *(iii)* who they were with (i.e. company, multiple choice, including *partners*, *children*, *other family members*, *colleagues or classmates*, *friends*, *other people they know*, or *strangers or themselves only*); and *(vi)* what they were currently doing (i.e. 42 activities, multiple choice). The exact timestamp of the response was recorded, and so was the precise location using GPS. The median number of responses was 16, with mean 46 and

[8]Participants could choose between 1, 2, 3, 4, or 5 messages per day and could specify daily start and end times to the nearest fifteen minutes. Notifications (pings) were similar to text messages in terms of sound, vibration, or both.

standard deviation 116. Note that, after completing the intake survey, respondents went on to complete a test experience-sampling survey. We routinely discard this first experience-sampling survey so as to focus on truly randomised surveys only. The randomisation algorithm is described in detail in Section 2.3.

Table **??** about here

Our outcome is feeling *happy*, which is obtained from a slider asking respondents: "Do you feel happy?". Answers range from zero ("Not at all") to 100 ("Extremely"), the initial position being the midpoint. Our variable of interest is *waiting or queueing*, which is a binary indicator that takes on value one if respondents selected "Waiting, queueing" when asked: "Just now, what were you doing?".

We merge these panel data with administrative data on meteorological conditions from the UK Meteorological Office Integrated Data Archive System (MIDAS) (Met Office, 2006a,b). These data include *air temperature* in degrees centigrade, *wind speed* in knots, a binary indicator for any *precipitation* during the hour prior to the response, binary indicators for any *cloud cover and sunshine*, and a binary indicator for *daylight*. Exploiting the exact geographical coordinates of responses, we link each response with the meteorological conditions reported by the weather station nearest to the response location at the nearest available date and time.

Our estimation sample is restricted to respondents who reply within 60 minutes to the most recent random ping and who complete the experience-sampling survey within five minutes. It covers the entire UK, including England, Wales, Scotland, and Northern Ireland. The sample contains $2,235,733$ observations from $30,936$ individuals over the course of eight years, i.e. from 2010 to 2017

2.2 Estimation

Drawing on this panel, our preferred specification is:

$$y_{it} = \alpha + \delta Waiting_{it} + \beta_1' A_{it} + \beta_2' P_{it} + \beta_3' L_{it} + \beta_4' C_{it} + \beta_5' M_{it} + r + t_s + t_{hd} + t_{dw} + t_m + t_y + u_i + \epsilon_{it} \tag{1}$$

where y_{it} is the *happiness* of respondent i at point in time t; $Waiting_{it}$ is a dummy that equals one if the respondent reports to be *waiting or queueing* when randomly messaged by the app, and zero else; and A_{it}, C_{it}, P_{it}, L_{it}, and M_{it} are vectors of contemporaneous controls. A_{it} includes dummies for 41 other activities the respondent may report to be doing (simultaneously) at the same time (e.g. a respondent may report to be *waiting or queueing* while *travelling or commuting* or while being at a *theatre, dance, or concert*, which may result in very different hedonic experiences of *waiting or queueing*). P_{it} includes dummies for the place the respondent reports to be at, which can be (exclusively) *at home*, *at work*, or *elsewhere*, whereas L_{it} includes dummies for the location, which can be (likewise exclusively) *indoors*, *outdoors*, or *in a vehicle*.[9] C_{it} includes dummies for the company the respondent reports to be in at the time, which can include multiple individuals: *partners*, *children*, *other family members*, *colleagues or classmates*, *friends*, *other people they know*, or *strangers or themselves only*. Finally, M_{it} are meteorological conditions, including *air temperature* in degrees centigrade (dummies for five-degree bands), *wind speed* in knots (dummies for four-knot bands), *precipitation* as a dummy for any rain during the hour prior to the response, *cloud cover and sunshine* as dummies for any cloud cover and for sunshine (no sun, any sun, and continuous sun), and *daylight* as a dummy for daylight at the response location, date, and time. Weather may be a potential confounder that may influence both happiness and the likelihood to be *waiting or queueing*. As with the other activities, the same logic applies: waiting outside in sunshine while talking to a friend may result in a very different hedonic experience of *waiting or queueing*) than waiting alone, outside in bad weather.

Apart from these time-varying confounders, we control for a wide range of spatial and temporal fixed effects. In particular, r are region fixed effects at the Middle Layer Super Output Area (MSOA) level that capture time-invariant unobserved heterogeneity in the geographical area where respondents report

[9] If respondents are working from home, they are prompted to select *at home*.

to be located when randomly messaged by the app. There are 8,925 such areas in our estimation sample. Moreover, t_s are holiday-season, t_{hd} hour-of-day, t_{dw} day-of-week, t_m month, and t_y year fixed effects that net out systematic differences across time and that flexibly account for time trends. Finally, u_i are individual fixed effects that capture time-invariant unobserved heterogeneity at the respondent level, e.g. time preferences, patience, genetic determinants and set points of happiness (cf. Okbay et al., 2016), or other individual-specific factors that may influence both happiness and may make some individuals more likely to be *waiting or queueing* than others. Our model is estimated using OLS, with robust standard errors clustered two-way at the region and respondent levels.

We are interested in the partial correlation coefficient δ: it is the within-person change in happiness associated with becoming engaged in the activity *waiting or queueing* (as opposed to not becoming engaged in that activity), holding everything else constant. It has a general interpretation, applying across *all* activities and their contextual characteristics. We are also interested in the response share s associated with *waiting or queueing* (i.e. the share of responses that respondents report to be *waiting or queueing* amongst all responses in percent, which we exploit to derive a duration in minutes and to conduct a social welfare analysis). For ease of exposition, we rewrite Equation 1 as:

$$y_{it} = \alpha + \delta Waiting_{it} + \beta' X_{it} + r + T + u_i + \epsilon_{it} \tag{2}$$

where X_{it} is a composite vector that includes A_{it}, P_{it}, L_{it}, C_{it}, and M_{it}, whereas the composite vector T includes t_s, t_{hd}, t_{dw}, t_m, and t_y.

2.3 Identification

Randomisation Algorithm. We rely on a simple, random, and non-predictable algorithm for scheduling messages asking participants to complete an experience-sampling survey. The algorithm has four steps:

first, it allocates three blocks of equal duration during the daily start and end time.[10] Second, it allocates a buffer at the end of each block (of 0.25× the block's duration) to avoid having two consecutive messages being too closely spaced in time. Third, it picks a random moment within each block, avoiding the block's buffer. Finally, it moves each randomly picked moment forward by the same amount of time, randomly chosen to be between zero and the block's duration, wrapping from the end of the day to its start, to reduce predictability while ensuring a uniform probability sample. The algorithm, thereby, effectively randomises messages *and* the daily start and end times. Figure **??** illustrates our randomisation algorithm for the case of three messages per day between 8am and 10pm.

Identifying Assumption. Our identification strategy exploits the randomisation of messages by the app. In particular, when exactly during the day (or night, if the smartphone is switched on and the app is active) a respondent is messaged to report on happiness y_{it}, place P_{it} and location L_{it}, company C_{it}, and activities A_{it} is random and hence orthogonal to the outcome of the respondent. When exactly a respondent is messaged is also orthogonal to the start and end time of each activity: random messaging ensures a uniform probability distribution, allowing us to capture a respondent at the start, end, or any time in-between with equal probability. Finally, when a respondent is messaged is orthogonal to other activities the respondent may be simultaneously engaged in at the time and the contexts in which these take place. Some activities and contexts, however, may be more likely to concur with *waiting or queueing* and, at the same time, may be correlated with happiness, which is why we routinely control for other activities, place and location, company, and meteorological conditions in X_{it} as well as region and time fixed effects r and T alongside individual fixed effects u_i throughout our regressions, to arrive at the net causal effect δ.[11]

Our identifying assumption is that selection into *waiting or queueing* (i.e. $Waiting_{it}$) and its actual reporting (i.e. $R(Waiting_{it})$, where $R(.)$ is the response function) is independent of happiness y_{it} or quasi-random, conditional on controlling for contextual characteristics X_{it}, region and time fixed effects r and T,

[10] Recall that the number of messages per day and the daily start and end time can be modified by participants, the default being two messages per day between 8am and 10pm.

[11] Note that our results remain qualitatively the same regardless of whether we include these controls or not, supporting the notion of exogeneity, even unconditionally. See Section 3.1 for these results.

and individual fixed effects u_i. That is,

$$y_{it} \perp Waiting_{it}, R(Waiting_{it}) | X_{it}, r, T, u_i. \tag{3}$$

Selection Into $\boldsymbol{Waiting_{it}}$. A common concern for identification is *reverse causality*, i.e. happier respondents may be systematically more likely to be *waiting or queueing* when randomly messaged by the app, or *vice versa*. In our case, this is less of a concern, for three reasons: first, controlling for individual fixed effects u_i nets out systematic differences in time-invariant set points of happiness between respondents. Second, to the extent that happiness is incidental when randomly messaged by the app, it is either random itself or random conditional on controlling for other activities the respondent may be simultaneously engaged in at the time and the contexts in which these take place (i.e. $E[y_{it}\epsilon_{it}|X_{it}, r, T] = 0$). Finally, if happier respondents were systematically more likely to be *waiting or queueing* when randomly messaged, it would likely lead to an underestimate of δ: by and large, the literature in economics and psychology finds that people in positive mood (i.e. who are happier) are more patient and less myopic (Ifcher and Zarghamee, 2011; Lerner et al., 2012; Haushofer and Fehr, 2014), suggesting that our identified effect is, if anything, likely to be a lower bound.[12] A similar logic applies to anticipation of waiting: assuming that unanticipated waiting most adversely affects happiness, anticipated waiting amongst our responses would likely lead to an underestimate of δ.

Selection Into $\boldsymbol{R(Waiting_{it})}$. While selection into *waiting or queueing* (i.e. $Waiting_{it}$) is less of a concern, selection into its actual reporting (i.e. $R(Waiting_{it})$) may be more problematic.[13] In particular, although the very nature of *waiting or queueing* (which is associated with idle time) makes it likely that respondents actually respond when randomly messaged by the app, there may be concern that the response

[12] Mechanisms include that happier people are less likely to crave for immediate rewards to compensate for their current unhappiness (Lerner et al., 2012), or that positive mood strengthens willpower (Ifcher and Zarghamee, 2011; Haushofer and Fehr, 2014).

[13] Note that controlling for individual fixed effects u_i also nets out systematic differences in response functions $R(.)$ between respondents, so that respondents should be equally likely to respond, with similar lags, when randomly messaged by the app.

function $R(.)$ depends on contextual characteristics that may be correlated with y_{it} (i.e. $R(Waiting_{it})+\mu_{it}$, where $E[y_{it}\mu_{it}] \neq 0$), and that there may be systematic over-reporting or under-reporting depending on these characteristics.[14] For example, respondents may be less likely to respond when waiting for a taxi with a friend after dinner, but more likely when waiting for the bus home by themselves after work. This may have implications for internal validity, by biasing δ, as well as for external validity, by yielding a skewed response share of s. Recall that it is entirely up to respondents to judge whether they consider their current activity to be *waiting or queueing*.

Again, controlling for other activities the respondent may be simultaneously engaged in at the time and the contexts in which these take place ensures that the response function $R(.)$ is conditionally uncorrelated with y_{it}, i.e. $E[y_{it}\mu_{it}|X_{it}, r, T] = 0$. We examine the robustness of δ in Section 3.1, where we look at unobservable selection and coefficient stability, by selectively excluding other activities, place and location, company, and meteorological conditions in X_{it} as well as region and time fixed effects r and T. As we shall see, our estimate of δ remains stable regardless of whether we include these controls or not. We then provide a bounding argument in line with Oster (2019), which suggests that unobservable selection plays, if anything, only a minor role.

Sample Selection. Another source of selection is sample selection, which may come in two flavours: first, there may be *out-of-sample selection*, which is related to internal validity. In our case, it may be a concern if respondents drop out of the sample for reasons that are related to *waiting or queueing* and that are, at the same time, correlated with happiness. We look into this point in Section **??**, where we regress the likelihood of dropping out on *waiting or queueing*. As we shall see, we do not find that *waiting or queueing* is a significant predictor of attrition. Note that, if respondents who are generally happier are more likely to drop out, or *vice versa*, it would be less of a concern, as we are looking at within-individual variation (i.e. changes rather than levels) and are controlling for time-invariant set points of happiness by including individual fixed effects u_i. Second, there may be *selection into the sample*, which is related to external

[14] If misreporting is random, it amounts to random measurement error and leads to attenuation bias, yielding a lower-bound estimate.

validity. We look into this point in Section **??**, where we compare our estimation sample with external data, by calculating normalised differences between the covariates from our intake and experience-sampling surveys and those in nationally representative household and time use data in the UK. As we shall see, our sample scores relatively high in terms of comparability.

3 Results

3.1 Waiting Time Estimate

Table 2 shows our waiting time estimate.

Table 2 about here

We find that *waiting or queueing* has a strong, significant negative effect on happiness: it decreases happiness measured on a zero-to-100 scale by about 3.6 points, holding other activities the respondent may be simultaneously engaged in, current place and location, company, and meteorological conditions as well as region and time fixed effects constant.

Waiting or queueing turns out to be the third least enjoyable activity, surpassed only by *being sick in bed* (−18.4) and *care or help for adults* (−3.9). It is followed by *travelling or commuting* (−1.9), *working or studying* (−1.6), and *admin, finances, organising* (−1.3). The most enjoyable activities, on the contrary, are *intimacy, making love* (+12.7), *sports, running, exercise* (+6.7), and *theatre, dance, concert* (+6.6). Activities are generally more enjoyed when being outdoors, somewhere else than at home or at work, and in the company of partners or friends. Appendix Table A1 shows the effects of all activities (including their response shares in percent and daily durations in minutes) as well as of place, location, and company on happiness.

3.2 The Value of Time (VOT)

To obtain our estimate of the VOT, we first calculate the marginal rate of substitution MRS between $Waiting_{it}$, which we estimate from Equation 2, and $Income_{it}$, which we estimate from an auxiliary income regression that we discuss in detail in Section **??**. We evaluate the MRS at the median income in the UK during our observation period, i.e. the years 2010 to 2017:

$$MRS = \frac{\frac{\partial y_{it}}{\partial Waiting_{it}}}{\frac{\partial y_{it}}{\partial Income_{it}}} \times Income_{UK} \tag{4}$$

$Waiting_{it}$ reduces happiness measured on a zero-to-100 scale by about 3.6 points, or 0.36 points when converted to the more conventional zero-to-ten scale (cf. Dolan and Metcalfe, 2012). On the contrary, we find that log annual net household income is associated with a rise in happiness of about 0.09 points. This implies that a 1% increase in income translates into a 0.0009 point increase in happiness. The median annual net household income in the UK during the period 2010 to 2017 was about £$18,200$ (\$$24,800$) (Office for National Statistics, 2020).

An important feature of experience-sampling is that activities are, at the time of reporting, *durationless*. This is a huge advantage: when randomly messaged by the app, respondents are not required to recall exactly how long they have been engaged in each of the activities they are currently doing (as they have to when using the day-reconstruction method (cf. Kahneman et al., 2004), which may lead to recall bias). Neither are they required to make a (possibly inaccurate or even biased) forecast of exactly how long they will continue to be engaged in each of their current activities. Yet, to calculate the MRS, we need to lend $Waiting_{it}$ a temporal dimension (as $Income_{UK}$ refers to annual income). Moreover, we need $Waiting_{it}$ and $Income_{UK}$ to refer to the same unit of time.

To lend $Waiting_{it}$ a temporal dimension, we exploit data on its response share $s_{Waiting}$, which amounts to 2.3%. Taking the average sleep time of 8.7 hours (523 minutes) in the UK per day (including both week days and weekends, cf. UK Time Use Survey 2014 – 2015), we obtain an average awake time of $(24\times60)-523 = 917$ (i.e. $Awake_{UK}$). Hence, a share of 2.3% corresponds to about $((24\times60)-523)\times0.023 =$ 21 minutes. That is, respondents report to be *waiting or queueing* for, on average, 21 minutes per day, either by itself or while doing other things. Recall that a 1% increase in income (£182) translates into a 0.0009 point increase in happiness. This is about £182/365/24/60 = 0.0003 per minute. Plugging these values into Equation 4 and multiplying it by the duration of 21 minutes yields the VOT_{20}:[15]

$$
\begin{aligned}
VOT_{20} &= MRS \times s_{Waiting} \\
&= (\frac{-0.36}{0.0009} \times 0.0003) \times 21 \\
&= -2.9
\end{aligned} \tag{5}
$$

That is, the average respondent in our estimation sample would be willing to pay about £2.9 (\$3.9) to avoid *waiting or queueing* for 21 minutes, or £8.3 (\$11.2) when standardised to one hour (i.e. VOT_{60} or simply VOT), assuming linearity when extrapolating. This is our preferred estimate for comparability with other studies. In Section 7, we compare our estimate with others in the literature. As we shall see, it closely resemble those from studies using revealed preferences.

3.3 The Value of Opportunity Time ($VOOT$)

Our parameter $Waiting_{it}$ resembles those in the literature, most of which look at the stated or revealed willingness to pay for a reduction in waiting time in a specific domain (e.g. commuting). If anything, our parameter is more generalisable, in that it applies across a broad range of activities and their contexts.

Yet, underlying both our parameter and those in the literature is that the VOT is estimated via a reduction in a bad. However, freeing up one additional hour of time not only reduces the displeasure from waiting one hour but also allows people to put that hour to alternative, ideally good, use, by spending

[15] The same monetary value can be obtained using a different time unit, e.g. hours instead of minutes.

it on more pleasurable activities instead. Our method gives us the unique opportunity to move beyond existing studies, which lack data on what people are doing beyond a narrow domain, by estimating a novel counterfactual: the *value of opportunity time ($VOOT$)*, defined as the value of the additional hour of free time that is obtained from reducing one hour of waiting time and that can be re-allocated to other activities. Assuming that people spend the additional hour of free time gained on activities that yield, on average, more pleasure than displeasure, we expect the $VOOT$ to be greater than the VOT, i.e. $VOOT > VOT$.

In obtaining this counterfactual, we make several assumptions: first, we assume that there are no binding constraints when re-allocating time from *waiting or queueing* to other activities (e.g. working time regulations that impose an upper limit on *working or studying*). This is likely to be satisfied: for example, for *working or studying*, which is the activity respondents report to spend most time in, the re-allocation of time amounts to about nine minutes only. Moreover, we assume that relative prices of activities in terms of pleasure or displeasure remain constant and that, as a result, selection into activities remains constant. Again, the rather small re-allocation of time makes this likely. Note that we re-allocate the additional hour of free time agnostically, i.e. *pro-rata* according to the initial response shares of other activities. Finally, we assume that observed selection into these other activities is a valid counterfactual. In other words, we assume that the activities respondents report to be engaged in are also those they would be engaged in had they marginally more time at their disposal. This is a conservative approach.

The $VOOT$ is obtained in three steps: first, we calculate the marginal rate of substitution (MRS_k) between each of the k other activities ($Activity_{it,k}$) and income ($Income_{it}$). We then re-allocate the additional hour of free time obtained from reducing one hour of *waiting or queueing* to each of the k other activities, *pro-rata* according to its initial response share s_k, using an activity-specific re-weighting factor t_k. Finally, we subtract the re-weighted sum of the marginal rates of substitution of all $k = 41$ other activities (i.e. the counterfactual) from the original sum of all $j = 42$ activities, which includes *waiting or queueing* (i.e. the as-is). This is shown in Equations 6 and 7, whereby Equation 7 shows the activity-specific re-weighting factor t_k:

$$
\begin{aligned}
VOOT &= \sum_{k=1}^{41} MRS_k \times t_k - \sum_{j=1}^{42} MRS_j \times 60 \\
&= \sum_{k=1}^{41} \left(\frac{\frac{\partial y_{it}}{\partial Activity_{it,k}}}{\frac{\partial y_{it}}{\partial Income_{it}}} \times Income_{UK}\right) \times t_k - \sum_{j=1}^{42} \left(\frac{\frac{\partial y_{it}}{\partial Activity_{it,j}}}{\frac{\partial y_{it}}{\partial Income_{it}}} \times Income_{UK}\right) \times 60
\end{aligned} \tag{6}
$$

and

$$
t_k = 60 + (Awake_{UK} \times s_{Waiting}) \times \frac{Awake_{UK} \times s_k}{\sum_{j=1}^{42} Awake_{UK} \times s_j - Awake_{UK} \times s_{Waiting}} \tag{7}
$$

where MRS_k is the marginal rate of substitution between $Activity_{it,k}$ and $Income_{it}$ for each other activity $k = \{1, 2, 3, ...41\}$ excluding *waiting or queueing*, evaluated at the median annual net household income in the UK during the period 2010 to 2017, i.e. $Income_{UK}$, and similarly for each activity $j = \{1, 2, 3, ...42\}$ including *waiting or queueing*. $Awake_{UK}$ is the average wake time in the UK per day. $s_{Waiting}$ and s_k are the response shares of $Waiting_{it}$ and $Activity_{it,k}$. Finally, t_k is the activity-specific re-weighting factor of activity k and 60 the constant weight.

We obtain a $VOOT$ of about £9.1 (\$12.4) per hour. It provides a natural upper bound to the monetary value of one hour of time, which lies within the interval $[VOT; VOOT]$, i.e. £$[8.3; 9.1]$ (\$$[11.2; 12.4]$).

4 Robustness

The last three sections, i.e. robustness, effect heterogeneity, and social welfare, are still work in progress and will be completed by the time of the conference.

5 Heterogeneity in Time Values

5.1 By Activity

5.2 By Person Characteristics

6 Social Welfare Analysis

7 Discussion

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References

Adler, M. D., Dolan, P., and Kavetsos, G. (2017). Would you choose to be happy? tradeoffs between happiness and the other dimensions of life in a large population survey. *Journal of Economic Behavior & Organzation*, 139:60–73.

Becker, G. S. (1965). A theory of the allocation of time. *Economic Journal*, 75(299):493–517.

Benjamin, D. J., Heffetz, O., Kimball, M. S., and Rees-Jones, A. (2012). What do you think would make you happier? what do you think you would choose? *American Economic Review*, 102(5):2083–2110.

Bradford, W. D., Dolan, P., and Galizzi, M. (2019). Looking ahead: Subjective time perception and individual discounting. *Journal of Risk and Uncertainty*, 58:43–69.

Bryson, A. and MacKerron, G. (2017). Are you happy while you work? *Economic Journal*, 127(599):106–125.

Buchholz, N., Doval, L., Kastl, J., Matějka, F., and Salz, T. (2020). The value of time: Evidence from auctioned cab rides. NBER Working Paper 27087, National Bureau of Economic Research.

Calfee, J. and Winston, C. (1998). The value of automobile travel time: implications for congestion policy. *Journal of Public Economics*, 69(1):83–102.

Deacon, R. T. and Sonstelie, J. (1985). Rationing by waiting and the value of time: Results from a natural experiment. *Journal of Political Economy*, 93(4):627–647.

DeSerpa, A. C. (1971). A theory of the economics of time. *Economic Journal*, 81(324):828–846.

DfT (2021a). Tag data book. https://www.gov.uk/government/publications/tag-data-book.

DfT (2021b). Tag unit a1.3: User and provider impacts. https://assets.publishing.service.gov.uk/government/uploads/system/uplo $tag - unit - a1 - 3 - user - and - provider - impacts - march - 2017.pdf$.

Dolan, P., Kavetsos, G., Krekel, C., Mavridis, D., Metcalfe, R., Senik, C., Szymanski, S., and Ziebarth, N. R. (2019). Quantifying the intangible impact of the olympics using subjective well-being data. *Journal of Public Economics*, 177:104043.

Dolan, P., Krekel, C., Shreedhar, G., Lee, H., Marshall, C., and Smith, A. (2021). Happy to help: The welfare effects of a nationwide micro-volunteering programme. CEP Discussion Paper 1772, Centre for Economic Performance.

Dolan, P. and Metcalfe, R. (2012). Measuring subjective wellbeing: Recommendations on measures for use by national governments. *Journal of Social Policy*, 41(2):409–427.

Edgeworth, F. Y. (1881). *Mathematical Psychics: An Essay on the Application of Mathematics to the Moral Sciences*. C. Kegan Paul and Co., London.

Evans, A. W. (1972). On the theory of the valuation and allocation of time. *Scottish Journal of Political Economy*, 19(1):1–17.

Fezzi, C., Bateman, J., and Ferrini, S. (2014). Using revealed preferences to estimate the value of travel time to recreation sites. *Journal of Environmental Economics and Management*, 67(1):58–70.

Fisher, I. (1892). *Mathematical Investigations in the Theory of Value and Prices*. PhD thesis, Yale University, New Haven.

Giurge, L. M., Whillans, A. V., and West, C. (2020). Why time poverty matters for individuals, organisations and nations. *Nature Human Behaviour*, 4:993–1003.

Goldszmidt, A., List, J. A., Metcalfe, R. D., Muir, I., Smith, V. K., and Wang, J. (2020). The value of time in the united states: Estimates from nationwide natural field experiments. NBER Working Paper 28208, National Bureau of Economic Research.

Haushofer, J. and Fehr, E. (2014). On the psychology of poverty. *Science*, 344(6186):862–867.

Hershfield, H. E., Mogilner, C., and Barnea, U. (2016). People who choose time over money are happier. *Social Psychological and Personality Science*, 7(7):697–706.

Ifcher, J. and Zarghamee, H. (2011). Happiness and time preference: The effect of positive affect in a random-assignment experiment. *American Economic Review*, 101(7):3109–2129.

INRIX (2019a). Inrix: Congestion costs each american nearly 100 hours, $ 1,400 a year. https://inrix.com/press-releases/2019-traffic-scorecard-us/.

INRIX (2019b). Inrix global traffic scorecard: Congestion cost uk economy £6.9 billion in 2019. https://inrix.com/press-releases/2019-traffic-scorecard-uk/.

Johnson, M. B. (1966). Travel time and the price of leisure. *Economic Inquiry*, 4(2):135–145.

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., and Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, 306(5702):1776–1780.

Kahneman, D. and Sugden, R. (2005). Experienced utility as a standard of policy evaluation. *Environmental and Resource Economics*, 32:161–181.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–292.

Kahneman, D. and Tversky, A. (1984). Choices, values, and frames. *American Psychologist*, 39(4):341–350.

Kahneman, D., Wakker, P. P., and Sarin, R. (1997). Back to bentham? explorations of experienced utility. *Quarterly Journal of Economics*, 112(2):375–406.

Killingsworth, M. A. (2021). Experienced well-being rises with income, even above $75,000 per year. *Proceedings of the National Academy of Sciences*, 118(4):e2016976118.

Kim, B. K. and Zauberman, G. (2013). Can victoria's secret change the future? a subjective time perception account of sexual-cue effects on impatience. *Journal of Experimental Psychology: General*, 142(2):328–335.

Krekel, C. and Zerrahn, A. (2017). Does the presence of wind turbines have negative externalities for people in their surroundings? evidence from well-being data. *Journal of Environmental Economics and Management*, 82:221–238.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, 112(2):443–478.

Lam, T. C. and Small, K. A. (2001). The value of time and reliability: measurement from a value pricing experiment. *Transportation Research Part E: Logistics and Transportation Review*, 37(2–3):231–251.

Lerner, J. S., Li, Y., and Weber, E. U. (2012). The financial costs of sadness. *Psychological Science*, 24(1):72–79.

Levinson, A. (2012). Valuing public goods using happiness data: The case of air quality. *Journal of Public Economics*, 96(9–10):869–880.

Lindqvist, E., Östling, R., and Cesarini, D. (2020). Long-run effects of lottery wealth on psychological well-being. *Review of Economic Studies*, 87(6):2703–2726.

Loewenstein, G. and Adler, D. (2005). A bias in the prediction of tastes. *Economic Journal*, 105(431):929–937.

Loewenstein, G., O'Donoghue, T., and Rabin, M. (2003). Projection bias in predicting future utility. *Quarterly Journal of Economics*, 118(4):1209–1248.

Loewenstein, G. and Prelec, D. (1992). Anomalies in intertemporal choice: Evidence and an interpretation. *Quarterly Journal of Economics*, 107(2):573–597.

Luechinger, S. (2009). Valuing air quality using the life satisfaction approach. *Economic Journal*, 119(536):482–515.

Luechinger, S. and Raschky, P. A. (2009). Valuing flood disasters using the life satisfaction approach. *Journal of Public Economics*, 93(3–4):620–633.

Maddison, D. and Rehdanz, K. (2011). The impact of climate on life satisfaction. *Ecological Economics*, 70(12):2437–2445.

Met Office (2006a). Midas uk hourly rainfall data. https://catalogue.ceda.ac.uk/uuid/7aaa582fb00246b794dc85950f1be265.

Met Office (2006b). Midas uk hourly rainfall data. https://catalogue.ceda.ac.uk/uuid/c58c1af69b9745fda4cdf487a9547185.

Odermatt, R. and Stutzer, A. (2019). (mis-)predicted subjective well-being following life events. *Journal of the European Economic Association*, 17(1):245–283.

Office for National Statistics (2020). Regional gross disposable household income: all itl level regions. https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/bulletins/householddi

Office for National Statistics (2021). Annual survey of hours and earnings time series of selected estimates. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/ashe1997to2015selected

Okbay, A., Baselmans, B. M. L., and De Neve, J.-E., e. a. (2016). Genetic variants associated with subjective well-being, depressive symptoms, and neuroticism identified through genome-wide analyses. *Nature Genetics*, 48(6):624–633.

Oort, C. J. (1969). The evaluation of travelling time. *Journal of Transport Economics and Policy*, 3(3):279–286.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2):187–204.

Prelec, D. (2004). Decreasing impatience: A criterion for non-stationary time preference and {"hyperbolic{" discounting. *Scandinavian Journal of Economics*, 106(3):511–532.

Read, D. (2001). Is time-discounting hyperbolic or subadditive? *Journal of Risk and Uncertainty*, 23:5–32.

Small, K. A., Winston, C., and Yan, J. (2005). Uncovering the distribution of motorists' preferences for travel time and reliability. *Econometrica*, 73(4):1367–1382.

Smeets, P., Whillans, A., Bekkers, R., and Norton, M. I. (2019). Time use and happiness of millionaires: Evidence from the netherlands. *Social Psychological and Personality Science*, 11(3):295–307.

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics Letters*, 8(3):201–207.

Tversky, A. and Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, 211(4481):453–458.

van Praag, B. M. S. and Baarsma, B. E. (2005). Using happiness surveys to value intangibles: The case of airport noise. *Economic Journal*, 115(500):224–246.

von Möllendorff, C. and Welsch, H. (2017). Measuring renewable energy externalities: Evidence from subjective well-being data. *Land Economics*, 93(1):109–126.

Welsch, H. and Ferreira, S. (2014). Environment, well-being, and experienced preference. *International Review of Environmental and Resource Economics*, 7(3–4):205–239.

Whillans, A. V., Dunn, E. W., Smeets, P., Bekkers, R., and Norton, M. I. (2017). Buying time promotes happiness. *Proceedings of the National Academy of Sciences*, 114(32):8523–8526.

Whillans, A. V., Macchia, L., and Dunn, E. W. (2019). Valuing time over money predicts happiness after a major life transition: A preregistered longitudinal study of graduating students. *Science Advances*, 5(9):eaax2615.

Whillans, A. V., Weidman, A. C., and Dunn, E. W. (2016). Valuing time over money is associated with greater happiness. *Social Psychological and Personality Science*, 7(3):213–222.

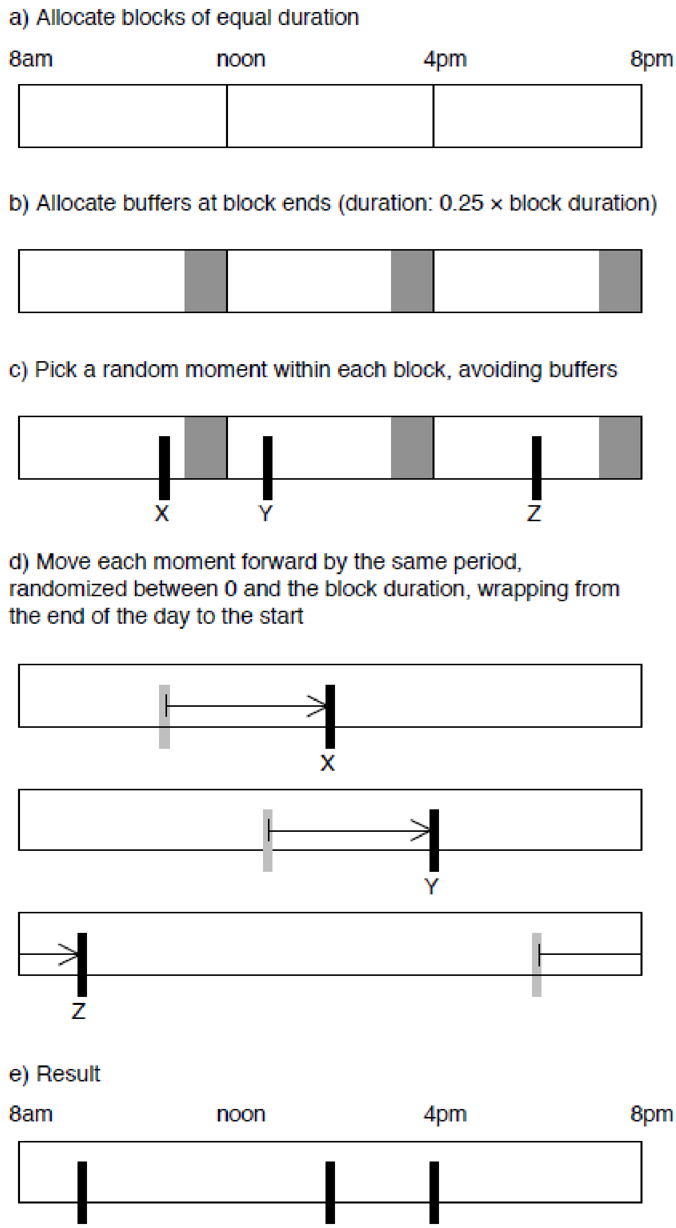
White, M. P. and Dolan, P. (2009). Accounting for the richness of daily activities. *Psychological Science*, 20(8):1000–1008.

Wilson, T. D. and Gilbert, D. T. (2003). Affective forecasting. *Advances in Experimental Social Psychology*, 35:345–411.

Wolff, H. (2014). Value of time: Speeding behavior and gasoline prices. *Journal of Environmental Economics and Management*, 67(1):71–88.

Xu, P., González-Vallejo, C., and Vincent, B. T. (2020). Waiting in intertemporal choice tasks affects discounting and subjective time perception. *Journal of Experimental Psychology: General*, 149(12):2289–2313.

Figure 1



Notes:

Source: Mappiness, own illustration.

Table 1A: Summary Statistics

	Mean	**Standard Deviation**	**Minimum**	**Maximum**	**Number of Observations**
Age	32.93	9.87	15	83	30,936
Gender					
… Male	0.51	0.50	0	1	30,936
… Female	0.49	0.50	0	1	30,936
Relationship Status					
… Not in Relationship	0.20	0.40	0	1	30,936
… In Relationship	0.80	0.40	0	1	30,936
… Never Married	0.60	0.49	0	1	30,936
… Married and Living With Spouse	0.32	0.47	0	1	30,936
… Married but Separated	0.03	0.16	0	1	30,936
… Divorced	0.05	0.21	0	1	30,936
… Widowed	0.00	0.06	0	1	30,936
Self-Assessed Health					
… Excellent Health	0.14	0.35	0	1	30,936
… Very Good Health	0.42	0.49	0	1	30,936
… Good Health	0.32	0.47	0	1	30,936
… Fair Health	0.09	0.29	0	1	30,936
… Poor Health	0.02	0.13	0	1	30,936
Employment Status					
… In Full-Time Education	0.12	0.32	0	1	30,936
… Employed or Self-Employed	0.80	0.40	0	1	30,936
… Unemployed and Looking	0.03	0.16	0	1	30,936
… Long-Term Sick or Disabled	0.01	0.10	0	1	30,936
… Looking After Family or Home	0.02	0.15	0	1	30,936
… Retired	0.01	0.09	0	1	30,936
… Other	0.01	0.12	0	1	30,936
Annual Gross Household Income					
… Under £8,000	0.06	0.23	0	1	30,936
… £8,000 to £11,999	0.03	0.17	0	1	30,936
… £12,000 to £15,999	0.04	0.20	0	1	30,936
… £16,000 to £19,999	0.04	0.21	0	1	30,936
… £20,000 to £23,999	0.06	0.23	0	1	30,936
… £24,000 to £31,999	0.11	0.31	0	1	30,936
… £32,000 to £39,999	0.11	0.32	0	1	30,936
… £40,000 to £55,999	0.19	0.39	0	1	30,936
… £56,000 to £71,999	0.14	0.35	0	1	30,936
… £72,000 to £95,999	0.10	0.30	0	1	30,936
… £96,000 or More	0.12	0.32	0	1	30,936
Number of Adults in Household					30,936
… 1	0.20	0.40	0	1	30,936
… 2	0.55	0.50	0	1	30,936
… 3	0.13	0.34	0	1	30,936
… 4 or More	0.12	0.32	0	1	30,936
Number of Children in Household					30,936
… None	0.71	0.45	0	1	30,936
… 1	0.13	0.34	0	1	30,936

Table 2: Waiting Time Estimate

	Happy (0-100)			
	(1)	(2)	(3)	(4)
$Waiting_{it}$	-3.31***	-3.11***	-3.11***	-3.62***
	(0.16)	(0.14)	(0.14)	(0.14)
Experience-Sampling Controls (X_{it})				
Other Activities	No	No	No	Yes
Company	No	No	No	Yes
Place	No	No	No	Yes
Location	No	No	No	Yes
Meteorological Controls (X_{it})				
Air Temperature	No	No	Yes	Yes
Wind Speed	No	No	Yes	Yes
Precipitation	No	No	Yes	Yes
Cloud Cover	No	No	Yes	Yes
Sunshine	No	No	Yes	Yes
Daylight	No	No	Yes	Yes
Spatial Controls (r)				
Region Fixed Effects	No	Yes	Yes	Yes
Temporal Controls (T)				
Holiday-Season Controls	No	Yes	Yes	Yes
Hour-of-Day Fixed Effects	No	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes
Month Fixed Effects	No	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Number of Individuals	30,936	30,936	30,936	30,936
Number of Observations	2,235,733	2,235,733	2,235,733	2,235,733
Adjusted R Squared	0.35	0.38	0.38	0.44
Adjusted R Squared Within	0.00	0.02	0.02	0.11
F-Test	419.87	87.14	81.80	190.45

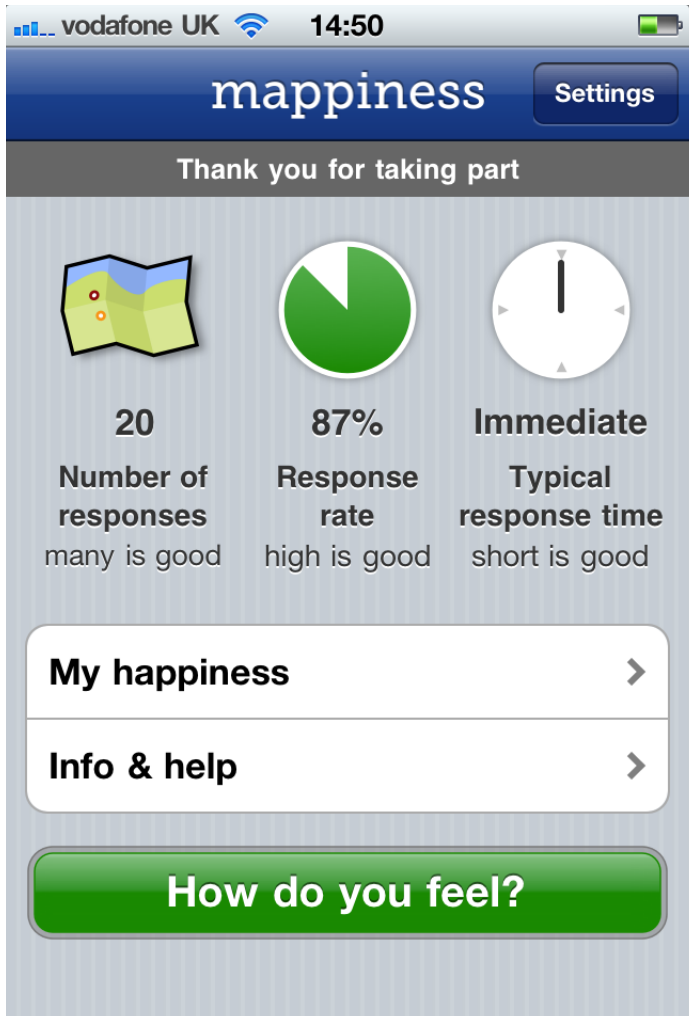
Robust standard errors clustered two-way at the region and respondent levels in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Income Estimate

	Happy (0-100)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Ln(EquivIncome_i)$	1.38***	1.17***	1.17***	1.30***	0.91***		0.95***
	(0.35)	(0.19)	(0.19)	(0.18)	(0.19)		(0.09)
$Ln(Income_i)$						0.91***	
						(0.20)	
Additional Individual-Level Controls (X_i)							
Age	No	No	No	Yes	Yes	Yes	Yes
Marital Status	No	No	No	Yes	Yes	Yes	Yes
Children	No	No	No	Yes	Yes	Yes	Yes
Health	No	No	No	Yes	Yes	Yes	Yes
Experience-Sampling Controls (X_{it})							
Other Activities	No	No	Yes	Yes	Yes	Yes	Yes
Company	No	No	Yes	Yes	Yes	Yes	Yes
Place	No	No	Yes	Yes	Yes	Yes	Yes
Location	No	No	Yes	Yes	Yes	Yes	Yes
Meteorological Controls (X_{it})							
Air Temperature	No	No	Yes	Yes	Yes	Yes	Yes
Wind Speed	No	No	Yes	Yes	Yes	Yes	Yes
Precipitation	No	No	Yes	Yes	Yes	Yes	Yes
Cloud Cover	No	No	Yes	Yes	Yes	Yes	Yes
Sunshine	No	No	Yes	Yes	Yes	Yes	Yes
Daylight	No	No	Yes	Yes	Yes	Yes	Yes
Spatial Controls (r)							
Region Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Temporal Controls (T)							
Holiday-Season Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Hour-of-Day Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	No	No	No	No	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Individuals	30,936	30,936	30,936	30,936	30,936	30,936	30,936
Number of Observations	2,235,733	2,235,733	2,235,733	2,235,733	2,235,733	2,235,733	2,235,733
Adjusted R Squared	0.00	0.13	0.13	0.20	0.21	0.21	-
Adjusted R Squared Within	0.00	0.02	0.02	0.10	0.12	0.12	-
F-Test	15.94	63.01	58.55	144.92	140.31	140.26	-

Appendix

Figure A1

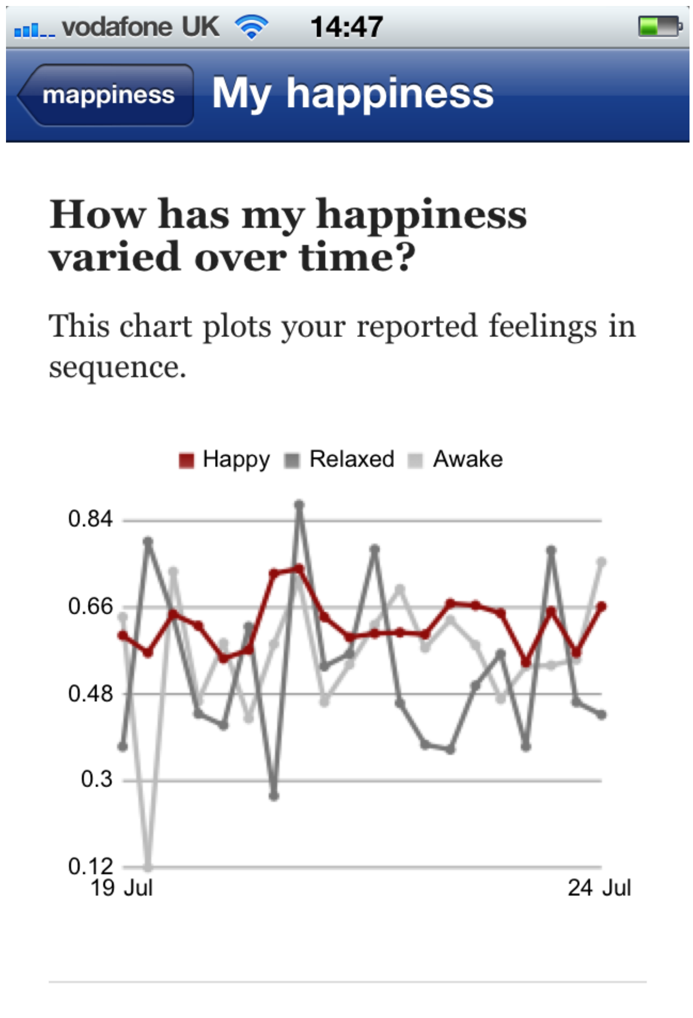


Notes:
Source: Mappiness, own illustration.

Figure A2

Notes:
Source: Mappiness, own illustration.

Figure A3



Notes:
Source: Mappiness, own illustration.

Figure A4

Notes:
Source: Mappiness, own illustration.

Table A1: Waiting Time Estimate – Full Table

	Happy (0-100)	Response Share s	Daily Duration (Minutes)
$Waiting_{it}$	-3.62***	2.32%	21.28
	(0.14)		
Other Activities (A_{it})			
$(\text{“}Working,\ studying\text{”})_{it}$	-1.61***	24.98%	229.17
	(0.08)		
$(\text{“}In\ meeting,\ seminar,\ class\text{”})_{it}$	0.30***	2.83%	25.96
	(0.11)		
$(\text{“}Travelling,\ commuting\text{”})_{it}$	-1.86***	8.98%	82.38
	(0.10)		
$(\text{“}Cooking,\ preparing\ food\text{”})_{it}$	2.24***	4.31%	39.54
	(0.08)		
$(\text{“}Housework,\ chores,\ DIY\text{”})_{it}$	-0.53***	5.19%	47.61
	(0.08)		
$(\text{“}Shopping,\ running\ errands\text{”})_{it}$	0.71***	3.01%	27.61
	(0.09)		
$(\text{“}Admin,\ finances,\ organising\text{”})_{it}$	-1.27***	3.92%	35.96
	(0.12)		
$(\text{“}Childcare,\ playing\ with\ children\text{”})_{it}$	2.77***	4.45%	40.82
	(0.14)		
$(\text{“}Petcare,\ playing\ with\ pets\text{”})_{it}$	3.19***	1.88%	17.25
	(0.17)		
$(\text{“}Care\ or\ help\ for\ adults\text{”})_{it}$	-3.85***	0.54%	4.95
	(0.62)		
$(\text{“}Sleeping,\ resting,\ relaxing\text{”})_{it}$	0.92***	9.86%	90.46
	(0.07)		
$(\text{“}Sick\ in\ bed\text{”})_{it}$	-18.37***	1.53%	14.04
	(0.29)		
$(\text{“}Meditating,\ religious\ activities\text{”})_{it}$	3.95***	0.31%	2.84
	(0.37)		
$(\text{“}Washing,\ dressing,\ grooming\text{”})_{it}$	2.01***	3.68%	33.76
	(0.08)		
$(\text{“}Talking,\ chatting,\ socialising\text{”})_{it}$	4.17***	14.93%	136.97
	(0.07)		
$(\text{“}Intimacy,\ making\ love\text{”})_{it}$	12.66***	0.56%	5.14
	(0.26)		
$(\text{“}Eating,\ snacking\text{”})_{it}$	2.01***	9.82%	90.09
	(0.06)		
$(\text{“}Drinking\ tea\ or\ coffee\text{”})_{it}$	1.39***	6.42%	58.90
	(0.06)		
$(\text{“}Drinking\ alcohol\text{”})_{it}$	3.61***	5.07%	46.51
	(0.09)		
$(\text{“}Smoking\text{”})_{it}$	0.45**	1.32%	12.11
	(0.18)		
$(\text{“}Texting,\ email,\ social\ media\text{”})_{it}$	0.92***	5.62%	51.56
	(0.08)		

Table A3: Robustness Check: Income Estimate – Comparison

	Happy (0-100) "Mappiness" Study (Present Paper)			
	Equivalised		Non-Equivalised	
	(1a)	(1b)	(2a)	(2b)
Log Annual Gross Household Income	1.38***	0.91***	1.77***	0.91***
Controls	No	Yes	No	Yes
Number of Individuals	30,936	30,936	30,936	30,936
Number of Observations	2,235,733	2,235,733	2,235,733	2,235,733

	"Track Your Happiness" Study (Killingsworth, 2021)			
	Restricted Sample		Unrestricted Sample	
	(3a)	(3b)	(4a)	(4b)
Log Gross Annual Household Income	1.13***	0.70***	0.91***	-
Controls	No	Yes	No	Yes
Number of Individuals	41,319	41,319	41,319	-
Number of Observations	2,100,828	2,100,828	2,100,828	-

	Non-Experience-Sampling Studies			
	Swedish Lottery Study (Lindqvist et al., 2020)		Annual Population Survey	
	11 Years Post-Win	All Years		
	(5a)	(5b)	(6a)	(6b)
Log Gross Annual Household Income	0.38*	0.16	0.29*	1.16***
Controls	Yes	Yes	No	Yes
Number of Individuals	1,273	3,327	34,911	34,911
Number of Observations	1,273	3,327	34,911	34,911

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A3 Notes

The "Mappiness" Study, which forms the basis of the present paper, is an app-based experience-sampling panel study in the UK. Its measure of annual gross household income from all sources is obtained from a categorical variable with twelve categories, whereby the midpoint of each category is used. To equivalise income, it is divided by the square root of the household size. The happiness measure is obtained from a slider that asks "Do you feel happy?", with answers from zero ("Not at all") to 100 ("Extremely"), whereby 50 is the initial position. The models are estimated using ordinary least squares, with controls including age, gender, marital status (including children), and health.

The "Track Your Happiness" Study, which is described in Killingsworth (2021), is an app-based experience-sampling panel study in the US. Its measure of annual gross household income from all sources is obtained from a categorical variable with fifteen categories (plus additional categories to capture high-income individuals), whereby the midpoint of each category is used. The happiness measure is obtained from a slider that asks "How do you feel right now?", with answers from "Very bad" to "Very good", whereby the initial position is close to "Very bad". The models are estimated using ordinary least squares, with controls including age, gender, marital status, and education level. The restricted sample includes employed, working-age US adults with a minimum annual income of $\$10,000$, the unrestricted sample all respondents.

The Swedish Lottery Study, which is described in Lindqvist et al. (2020), is a long-run follow-up survey of a large number of lottery players in Sweden. The study exploits random allocation of prizes to winners conditional on different lottery rules, so that the income coefficient can be interpreted as causal. Its measure of income is a windfall sum of $\$100,000$, measured between five to 22 years after the lottery win. Its happiness measure is obtained from an eleven-point Likert-scale question asking "Taking all things together, how happy would you say that you are?", with answers ranging from zero ("Extremely unhappy") to ten ("Extremely happy"). All years include 1994 to 2011, earlier years 1994 to 2005. The models are estimated using ordinary least squares, with controls including age, gender, marital status (including children), education, migration status, and capital and labour income.

The Annual Population Survey are cross-section data that combine and extend the quarterly Labour Force Survey in Great Britain. Its measure of annual gross household income is based on the gross weekly pay in the main job of all respondents who are employees and those on a government scheme, multiplied by 52. The happiness measure is obtained from an eleven-point Likert-scale question asking "Overall, how happy did you feel yesterday?", with answers ranging from zero ("Not at all") to ten ("Completely"). The models are estimated using ordinary least squares, with controls include age, gender, marital status, health, and education (i.e. the combined controls from the "Mappiness" and "Track Your Happiness" experience-sampling studies), as well as total usual hours worked to account for differences in time use, which is similar to controlling for activities in experience-sampling studies. We weigh observations using integrated household weights.