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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 over eight years randomly asked a panel of 30, 936 UK residents (N = 2, 235, 733) about their momentary feelings and activities to estimate the value of time (*VOT*), a key input into cost-benefit analyses. Exploiting the randomised timing of surveys for identification, we arrive at a *VOT* of £12.2 ($15.3) per hour of waiting, £8.4 ($10.5) per hour of commuting, and £17.2 ($21.5) per hour of waiting during commuting (e.g. due to congestion). This resembles estimates from studies using revealed preferences, suggesting that using hedonic experiences leads to similar results as observed behaviour. Our unique data and method also allow us to estimate the *VOT* for 40 other daily activities as well as their interactions. We are the first to value time (or indeed anything) using hedonic experiences in real-time, which has the potential to value other intangibles too.

Key words: value of time, time savings, experience-sampling, experiential valuation, cost-benefit analysis, waiting, commuting
JEL Classification: R4; D61; I31

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1 Introduction

How individuals spend their time determines to a large extent how satisfied they are with their lives (Smeets et al., 2019; Sharif et al., 2021), 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; Whillans and West, 2022).[1]

To the extent that markets insufficiently (or even fail to) provide the means for people to optimally allocate their time (e.g. through investments into time-saving infrastructure such as high-speed rail), 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 (149 hours in London, compared to 98 in Edinburgh or 75 in Hull). In the US, this 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 time-saving investments. But how shall economists value time and potential time savings, key inputs into cost-benefit analyses?

Time has received rather little attention in economics, relative to other concepts.[2] Yet, there exists an established literature that attempts to put a price tag on time, dating back to seminal work by Becker (1965). Here, market goods and time are inputs into household production and a time budget is split between labour and leisure such that leisure time, in general terms, is optimally valued at the prevailing wage rate (i.e. the opportunity cost of leisure). Other classic time allocation studies extended this work, for example 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; DeSerpa (1971), who introduces constraints in time allocation; Pollack and Wachter

[1] For a review of how people in North America and other developed countries spend their time, including differences between them, see Hamermesh (2019).

[2] A concept that has been put forward more recently by Krueger et al. (2009) is *National Time Accounting (NTA)*: the idea is to use data on the hedonic experiences of individuals during various uses of their time to measure societal welfare.

(1975), who introduce joint household production; or Cauley (1987), who identifies cases where the value of leisure time deviates from the wage rate (e.g. people not working at market wages).

Most empirical studies attempting to estimate the *value of time (VOT)* come from transport economics and look at reductions in travel or waiting time during commuting (e.g. De Vany (1974) looks at air, McFadden (1974) at urban travel).[3] They can be broadly categorised into two streams.

The first relies on *stated preferences* and includes discrete choice experiments or contingent valuation studies, which directly ask people how much they would be willing to pay for, for example, a hypothetical reduction in travel time due to a new road (Calfee and Winston, 1998). The second relies on *revealed preferences* and consists of 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 geographical 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 $VOTs$ to be less than 25% of the mean wage rate, observed behaviour often reveals much higher values, typically in excess of 75%.[4]

Overcoming issues such as attitude expression or strategic answers, studies relying on revealed preferences 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 options, for example between different waiting times and prices 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 problems.

First, research on heuristics and biases has shown that how options are presented has a significant influence on choices, e.g. whether options are presented in a gain or loss frame, like "time saved" or

[3]A (much) smaller set of studies look at reductions in treatment or waiting time during medical care (cf. Cauley, 1987; Borisova and Goodman, 2002), some at consumer behaviour (e.g. search time for consumer products) (cf. Crafton, 1979).

[4]Appendix Table A8 includes a full review of the literature, including estimates by valuation method.

"time lost" (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981; Kahneman and Tversky, 1984). Likewise, cognitive biases in intertemporal choice (e.g. present bias) are likely to also systematically bias how individuals value time itself (Thaler, 1981; Loewenstein and Prelec, 1992; Laibson, 1997). Second, what constitutes travel or waiting time, or even commuting itself, is 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 an activity is experienced, e.g. time spent waiting with a loved one may be experienced differently than time spent waiting alone, or may not be perceived as waiting at all (Kim and Zauberman, 2013; Xu et al., 2020). Third, there is a large body of evidence on prediction errors in economics (Loewenstein et al., 2003; Loewenstein and Adler, 2005) and psychology (Wilson and Gilbert, 2003), showing that individuals make large, systematic errors when predicting the welfare consequences of particular decisions and events (cf. Odermatt and Stutzer, 2019).

We thus propose an alternative method to estimate the VOT: *experiential valuation* based on experience-sampling. Our method does not rely on choice architecture and how options are presented to individuals. Moreover, it allows individuals to judge for themselves what constitutes a particular use of their time (e.g. whether commuting is really being perceived as commuting). Most importantly, it does not require individuals to predict the welfare consequences of different options at the point of decision-making but, instead, looks at their hedonic experiences once they have made their decisions. Or, put differently, it does not rely on how individuals *think* what the welfare consequences of different options will be but, instead, relies on how they actually *feel* once they have made their decisions.[5]

The idea behind experience-sampling goes back to the early economist Francis Y. Edgeworth (1845-1926) who, in his treatise *Mathematical Psychics* (1881), argued that new technical developments would eventually make it possible to develop a *hedonimeter*, which would allow economists to directly measure utility on a physiological basis. Already acknowledging that individuals are prone to making systematic errors, Edgeworth envisioned the hedonimeter as a "psychophysical machine,

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

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 builds on Edgeworth's hedonimeter, with three key differences: while Edgeworth's vision was certainly to directly measure utility, we do not require our measure of hedonic experiences – whether an individual feels happy – to be equal to utility. For our purpose, it is sufficient that individuals care about their experiences and that these matter for their behaviour. There is now evidence from 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, 2022), with implications for their behaviour across a wide range of domains (cf. De Neve and Oswald, 2012; Oswald et al., 2015; Liberini et al., 2017; Ward, 2020; Kaiser and Oswald, 2022).[6] The remaining two differences are more practical: we collect data using self-reports, in discrete rather than continuous time. Our method differs from the day-reconstruction method by Kahneman et al. (2004) and time use surveys in that it collects data on activities and feelings in real-time, rather than asking about them retrospectively in form of diaries.

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

We use these rich panel data to estimate the VOT for 42 daily activities (including *commuting or travelling*, *working or studying*, *care or help for adults*, and many more). We start with the activity *waiting or queueing* to estimate the VOT associated with potential time savings from reducing waiting time in general. We then look at the 41 other daily activities as well as interactions between them. We are particularly interested in commuting and the interaction between waiting

[6] Edgeworth himself suggested 'happiness' for his hedonimeter, being fully aware of its imperfections. Like many of his contemporaries, he was rather pragmatic, arguing that the "greater uncertainty of hedonimetry [...] 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 commuting to estimate the VOT for commuting and potential time savings in commuting. This estimate can be compared to studies in transport economics that look at reductions in travel or waiting time during commuting. Our method, however, is more flexible than existing studies, in that it can be used to estimate the VOT for all possible (combinations of) activities and their contexts (e.g. working during commuting, being accompanied by a colleague).

Our method has three steps: exploiting the randomised timing of surveys for identification, we first estimate the effect of each activity and income on respondents' happiness. We then calculate the marginal rate of substitution between each activity and income to obtain the income equivalent of each activity, standardising it to 60 minutes for comparability to the literature. Finally, we obtain the VOT for each activity by subtracting from the income equivalent of that activity the weighted average of the income equivalents of all the other activities (i.e. the counterfactual). Hence, the VOT for each activity is the monetary value of spending 60 minutes in that activity as opposed to spending them doing something else. Our regressions look at within-individual variation, controlling for other activities respondents may be simultaneously engaged in, where they currently are, who they are with, meteorological conditions, and region and time fixed effects.[7]

We arrive at a VOT of £12.2 ($15.3) per hour of waiting, £8.4 ($10.5) per hour of commuting, and £17.2 ($21.5) per hour of waiting during commuting.[8] That is, per individual, the monetary value of spending 60 minutes in *commuting or travelling* as opposed to spending them doing something else is worth £8.4 ($10.5) on average, and spending 60 minutes waiting during commuting (e.g. due to congestion) even £17.2 ($21.5), which suggests a high value of potential time savings in commuting (e.g. due to investments into time-saving infrastructure). Our estimate is similar to Goldszmidt et al. (2020) who in field experiments experimentally manipulate bundles of waiting times and prices offered to users of the Lyft ride-sharing app, estimating the VOT for reductions in waiting time during commuting to be $19 in the US in 2020. This suggests that using hedonic experiences leads to similar (though not identical) results as observed behaviour. Yet, our estimate is higher than values currently used by UK Government, suggesting that UK Government may, at

[7]Our results are similar regardless of whether we include these (potentially mediating) controls or not.

[8]All $ figures are converted from £using an exchange rate of 1 : 1.25, current at June 1, 2023.

least to some extent, underestimate the benefits of potential time savings in commuting.[9] Compared to hourly wages in the UK in 2022, our estimate is about 59% of the median wage, which is £14.8 ($18.5) (Office for National Statistics, 2022).

Our paper contributes to the literature that attempts to estimate the VOT, which mostly looks at reductions in travel or waiting time during commuting, 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, which also allows us to move beyond existing studies that lack data on what people are actually doing beyond a narrow domain such as commuting. Our sample is also broader, covering a wider range of individuals than studies relying on smaller experiments or specific groups such as ride-share users. Our paper also contributes to the literature, mostly in public and environmental economics, that uses accounts of self-reported life satisfaction for non-market or intangible 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; Krekel et al., 2021; Goebel et al., 2022). This approach to non-market valuation has become accepted in the literature, and is now part of official UK Treasury guidelines for policy appraisal and evaluation (HM Treasury, 2021b,a). Our paper shows that hedonic experiences in real-time can be used as a complementary approach, which could be particularly useful for activities that are too granular to be captured by data on self-reported life satisfaction.[10]

Our paper is the first to exploit hedonic experiences in real-time to value time (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*.

[9]The UK Department for Transport (DfT) uses a value of time during commuting (when private, which includes all trips to and from work during non-work time) of £12.9 ($16.1), as well as a separate employer's business value of time during commuting (which includes all business trips) of £10.3 ($12.9) for trips by car and £8.9 ($11.1) for trips by rail, all in 2022 prices (DfT, 2022, 2023).

[10]We will discuss this point in more detail in Section 6.

2 Data

We use individual-level panel data collected via a smartphone app called *Mappiness*.[11] The app was developed for Apple's iPhone and was distributed via its App Store from 2010 onwards, at no charge.[12] Developed at the London School of Economics, it gained popularity in the UK thanks to broad coverage in social and traditional media. For example, the app was highlighted in the *Featured* section of the App Store for more than two weeks after its launch, and also featured on social networking sites (i.e. Facebook and Twitter) as well as on television (i.e. the BBC), radio, and in the mainstream press. As a result, a broader range of individuals selected into using the app compared to other, typically much smaller experience-sampling studies (mostly in psychology). The app was described to users as a "research project" that "maps happiness across space in the UK", offering users "interesting information about their own happiness [...]", including "when, where and with whom they are happiest". Regular interaction with the app was incentivised by providing participants with frequent, 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. Overall, our sample includes $30,936$ unique respondents and a total of $2,235,733$ responses, covering the entire UK (including England, Wales, Scotland, and Northern Ireland) over the course of eight years, i.e. from 2010 to 2017.[13] The median number of responses are 161, with mean 72 and standard deviation 162. Appendix Figures A1 to A3 show screenshots of the app.

2.1 Intake Survey

After downloading the app, participants (who had to be above 18 years of age) first gave their informed consent to take part in the study, which covered anonymisation as well as secure transfer and storage of data. They were then forwarded to a short intake survey which was integrated into the app and which asked about demographic and socio-economic characteristics (i.e. age,

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

[12] More specifically, the app was downloadable from August 6, 2010, until February 4, 2017.

[13] We restrict our sample to UK residents (who are the vast majority), though the app could, in principle, also be downloaded from abroad.

gender, marital status, health, employment status, and overall life satisfaction) as well as household characteristics (i.e. household income and the number of adults and children in the household). This survey was completed only once, before data on hedonic experiences were collected, to not prime respondents when asking them about their momentary feelings and activities. The entire sign-up process typically took no longer than five minutes.

Appendix Table A1 shows summary statistics of our intake survey. On average, respondents are 33 years old (standard deviation of ten), equally likely to be male or female, 80% likely to be in a relationship (though only 32% are married and 29% have children), and most consider themselves to be in good (32%) or very good health (42%), some even in excellent health (14%). About 80% are employed or self-employed, 12% in full-time education, and 3% unemployed, with an average annual gross household income of £38,400 ($48,000). About a quarter of respondents are from London, the others are broadly balanced across the remaining regions of the UK.

In a robustness check in Section 5.3, we test our intake survey for external validity with respect to the UK general population, by comparing the demographic and socio-economic characteristics as well as household characteristics in our data with those in the nationally representative UK Household Longitudinal Study ("Understanding Society"). As we shall see, our data score relatively high in terms of external validity.

2.2 Experience-Sampling Survey

After completing the intake survey, the app started operating: participants were messaged at *random* points in time (the default being twice a day between 8am and 10pm) and asked to complete a short experience-sampling survey.[14] This randomly recurring survey asked participants about, in the following order to avoid priming: *(i)* how *happy* they felt in that particular moment (i.e. hedonic experiences); *(ii)* where they currently were (i.e. places and locations, single choices which could be exclusively *at home*, *at work*, or *elsewhere*, as well as *indoors*, *outdoors*, or *in a vehicle*); *(iii)* who they were with (i.e. company, a multiple choice which could include *partners*, *children*,

[14] 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 were similar to text messages in terms of sound and vibration.

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 daily activities, a multiple choice to account for multi-tasking).[15] The exact timestamp of the response was recorded, and so was the precise location using GPS.[16] We restrict our sample to responses given within 60 minutes to the most recent random message and to experience-sampling surveys which were completed within five minutes.[17] The randomisation algorithm inside the app is described in Section 3.2. The order of items (e.g. the different activities) was thematically grouped and purposefully *not* randomised, a design choice aimed to make it easier for respondents to complete each experience-sampling survey quickly. When setting up the app, respondents were encouraged to complete the surveys as soon as possible upon receipt. Each typically took no longer than 30 seconds.

Appendix Table A2 shows summary statistics of our experience-sampling survey. On average, respondents spend large amounts of time on work and related activities: 25% of responses come from *working or studying*, compared to 9% from *commuting or travelling*. An additional 11% come from communicating with others or searching for information, including writing e-mails, text messaging, using social media, or browsing the internet. However, respondents also spend large amounts of time on leisure: 18% of responses come from watching television or movies alone, another 20% from eating or relaxing in one form or another. In terms of company, most respondents are not alone: 24% are with their partner when randomly messaged by the app, 17% with colleagues or classmates, and 9% with friends. When it comes to their place and location, 51% are at home and the remainder split equally between at work and elsewhere. The vast majority is indoors (84%), with only 8% being outdoors and 7% in a vehicle. Note that response shares add up to 1.73, suggesting that respondents are, on average, engaged in 1.73 activities at the same time (i.e. multi-tasking).

In another robustness check in Section 5.3, we also test our experience-sampling survey for external validity with respect to the UK general population, by comparing the activities in our

[15] If respondents are working from home when randomly messaged by the app, they were prompted to select *at home*. If they were driving a vehicle, they were asked to complete the survey once they had completed their journey.

[16] Note that, after completing the intake survey, respondents went on to complete a test experience-sampling survey. We routinely discard this survey to focus on randomly timed surveys only.

[17] A cut-off of 60 minutes to the most recent message is chosen so that responses more accurately reflect a probability sample of the moments in a respondent's life. A cut-off of five minutes to survey completion is chosen so that hedonic experiences remain temporarily matched to activities, place and location, and company, as well as GPS location.

data with those in the nationally representative UK Time Use Survey.[18] As we shall see, our data score again high in terms of external validity.

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 variables of interest are 42 daily activities for which we estimate the VOT, starting with the activity *waiting or queueing*. We use a binary indicator for each activity. For *waiting or queueing*, for example, the indicator takes on one if a respondent selected "Waiting, queueing" when asked: "Just now, what were you doing?", and zero else.[19]

2.3 Weather Data

We merge the individual-level panel data collected via our smartphone app 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 (binary indicators for five-degree bands), *wind speed* in knots (binary indicators for four-knot bands), *precipitation* as a binary indicator for any rain during the hour prior to the response, *cloud cover and sunshine* as binary indicators for any cloud cover and for sunshine (no sun, any sun, and continuous sun), and *daylight* as a binary indicator for daylight at the response location, date, and time. 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.

[18] Contrary to time use surveys, which ask respondents retrospectively about their feelings and activities in form of diaries, experience-sampling surveys may be subject to reactivity, in that the very act of asking respondents about their momentary feelings may affect their feelings. We expect this to be a minor issue, as respondents in our sample are asked repeatedly and the novelty of asking arguably wears off after a while.

[19] The Online Appendix includes links to the description of the app in Apple's App Store, to the informed consent form, and to both intake survey and experience-sampling survey.

3 Empirical Strategy

3.1 Estimation

We estimate the VOT for 42 daily activities, starting with the activity *waiting or queueing*. Our baseline specification is:

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

where y_{it} is the *happiness* of respondent i at time t; $Waiting_{it}$ is a dummy that takes on one if a 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 controls.[20] A_{it} includes dummies for the 41 other daily activities a respondent may report to be doing at the time (e.g. a respondent may report to be *waiting or queueing* while *commuting or travelling* or while being at a *theatre, dance, or concert*, which may result in different hedonic experiences of *waiting or queueing*).[21] P_{it} includes dummies for the place a respondent reports to be at (e.g. *at work*), whereas L_{it} includes dummies for the location (e.g. *indoors*). C_{it} includes dummies for the company a respondent reports to be in at the time (e.g. *colleagues or classmates*). Finally, M_{it} includes dummies for meteorological conditions (e.g. *precipitation*). Weather may be a potential confounder that may influence both happiness and the likelihood to engage in certain activities, including *waiting or queueing*. As with other activities, the same logic applies: waiting outside in sunshine while talking to a friend may result in a different hedonic experience of *waiting or queueing*) than waiting alone, outside in the rain.[22]

Apart from these time-varying confounders, we control for region and time fixed effects. In particular, r are region fixed effects at the Middle Layer Super Output Area (MSOA) level that

[20] In Section 5.1, we show that our results are robust to excluding both time-varying experience-sampling controls (i.e. A_{it}, C_{it}, P_{it}, L_{it}, and M_{it}) and spatial and temporal fixed effects.

[21] Individuals may also derive pleasure or displeasure from anticipating or remembering activities. Our method, however, is only able to capture *current* activities.

[22] We cannot control for time-varying individual and household characteristics as the intake survey was completed only once. However, we expect confounding from changes in these characteristics to be a minor issue: the median days of participation were 52 (mean 143 and standard deviation 467).

net out systematic differences in time-invariant unobserved heterogeneity in the local area where respondents report to be in when randomly messaged by the app. There are $8,925$ such areas in our sample.[23] 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 flexibly account for time trends. Finally, u_i are individual fixed effects that net out systematic differences in time-invariant unobserved heterogeneity at the respondent level, e.g. time preference or patience (cf. Ifcher and Zarghamee, 2011; Lerner et al., 2012; Haushofer and Fehr, 2014), genetic determinants or set points of happiness (cf. Tellegen et al., 1988; Rietveld et al., 2013; Okbay et al., 2016). Our model is estimated using OLS, with robust standard errors clustered two-way at the region and respondent levels.

We are interested in coefficient δ: it is the within-individual change in happiness associated with becoming engaged in the activity *waiting or queueing*, holding everything else constant. We are also interested in the response share s: it is the share of responses that are reported to be in that activity amongst all responses. For brevity, 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}, T a composite vector that includes t_s, t_{hd}, t_{dw}, t_m, and t_y.

3.2 Identification

The randomised timing of surveys aims to ensure that, first, responses more accurately reflect a probability sample of the moments in a respondent's life, and second, respondents do not systematically select into surveys based on their current happiness (e.g. any time respondents may be bored and hence unhappy, they may be systematically more likely to take out their phone, use the app, and complete a survey).

[23] MSOAs capture between $2,000$ and $6,000$ households and have a resident population between $5,000$ and $15,000$ individuals.

Randomisation Algorithm. We rely on a simple and non-predictable randomisation algorithm for randomising the timing of surveys. It has four steps: first, it allocates three blocks of equal duration during the daily start and end time. Second, it allocates a buffer at the end of each block (of 0.25× the block's duration) to avoid having two consecutive surveys 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, which is again 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 the timing of surveys *and* the daily start and end times. Figure 1 illustrates our algorithm for the case of three surveys per day between 8am and 10pm.

Identifying Assumption. Our identification strategy exploits the randomised timing of surveys. In particular, when exactly during the day (or night, if the smartphone was switched on) a respondent was 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 happiness of a respondent. When exactly a respondent is messaged is also orthogonal to the start and end time of each activity, 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 a respondent may be engaged in at the same time and the contexts in which these take place. Some activities and contexts, however, may be systematically 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. The same logic applies to all the other activities.

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, 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. Respondents who are unhappier – permanently – may be systematically more likely to engage in certain activities than others, or *vice versa*. When it comes to selection into $Waiting_{it}$, for example, people who have a chronic illness may be permanently unhappier and, at the same time, may be systematically more likely to be waiting at the doctor's office, potentially biasing δ. When it comes to $R(Waiting_{it})$, this may also affect the likelihood to actually report to be waiting, potentially biasing s.

Controlling for individual fixed effects u_i nets out such systematic differences in time-invariant unobserved heterogeneity at the respondent level. It also nets out systematic differences in response functions $R(.)$ between respondents, so that respondents should be equally likely to respond, with similar response times.

Some activities and the contexts in which these take place may be systematically more likely to concur with others and, at the same time, may be correlated with happiness, temporarily. Again, when it comes to selection into $Waiting_{it}$, people may be more likely to be waiting during commuting, in a vehicle, with strangers or by themselves, potentially biasing δ.[24] A similar argument can again be made for $R(Waiting_{it})$ and s.[25]

Hence, we account for other activities a respondent may be engaged in at the same time and the contexts in which these take place, by routinely controlling for X_{it} throughout our regressions. This includes 41 other activities in A_{it}, seven types of company in C_{it}, three places in P_{it} and three locations in L_{it}, and meteorological conditions in M_{it} (which may be relevant for spending time outdoors). Importantly, respondents have the option to select two residual activities if none of the activities fits to their current activity: *something else* and, if they wish to report a customised activity, a free text. A residual category also exists for location: *elsewhere*. Unobservable activities

[24]Recall that it is entirely up to respondents to judge whether they consider their current activity to be *waiting or queueing*.

[25]For *waiting or queueing*, one could argue that its very nature (which is associated with idle time) makes it more likely that respondents actually respond when randomly messaged by the app.

and locations should, in principle, be captured by these.[26]

Still, there may be residual selection. We thus examine the robustness of our coefficient δ in Section 5.1, 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 from Equation 2. As we shall see, our coefficient δ remains stable regardless of whether we include these controls or not, with the effect size changing by less than 10%.

4 Results

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 a respondent may be simultaneously engaged in, current place and location, company, and meteorological conditions constant and controlling for region, time, and individual fixed effects. Table 1 shows our results.

Table 1 about here

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). However, less than five percent of responses come from these activities.[27] It is followed by *commuting or travelling* (−1.9), *working or studying* (−1.6), and *admin, finances, or organising* (−1.3), which show some of the highest response shares, in particular *working or studying* (25%) and *commuting or travelling* (9%). The most enjoyable activities, on the contrary, are *intimacy* (+12.7), *sports, running, or exercise* (+6.7), and *theatre, dance, or concert* (+6.6). Most responses come from moderately enjoyable activities, though, in particular *watching TV or movies* (+2.3, 18%) and *talking, chatting, or socialising* (+4.2, 9%).

[26] When it comes to $Waiting_{it}$, individuals may form expectations regarding waiting times. To the extent that waiting is experienced as negative, and actual waiting is shorter than expected, reference-dependent preferences suggest that individuals may be less negatively affected, and *vice versa* (Kőszegi and Rabin, 2006). Unfortunately, our data do not capture expectations. Note that individuals may have engaged in mitigating behaviour to avoid waiting in the first place, if expected.

[27] To our knowledge, our paper is the first to document how people actually feel when *waiting or queueing*, exploiting the only dataset that includes this variable.

Activities are generally more enjoyed when being outdoors, somewhere else than at home or at work, and in the company of partners or friends.

4.1 VOT for Waiting

We now calculate the VOT for each activity, starting with *waiting or queueing*, i.e. $VOT_{k=1}$. It is defined as the monetary value of spending 60 minutes in the activity *waiting or queueing* as opposed to the average monetary value of all the other activities, weighted by their relative frequency.[28] By using a weighted average of all the other activities, we assume that observed selection into these other activities constitutes a valid counterfactual, which is an agnostic approach.

We find that spending 60 minutes in the activity *waiting or queueing* as opposed to spending them doing something else is worth £−12.2 (\$ − 15.3). The negative sign suggests that there is an opportunity cost to waiting, and that respondents may be better off (in terms of their hedonic experiences) spending their time doing something else. Put differently, a respondent who is waiting for 60 minutes would need to be compensated £12.2 (\$15.3) to achieve the same level of happiness if they were not waiting.

To obtain $VOT_{k=1}$, we use our coefficients from Equation 2 and first calculate the marginal rate of substitution $MRS_{k=1}$ between *waiting or queueing* and income to arrive at an income equivalent of the activity. Then, we subtract from that income equivalent the average income equivalent of the 41 other daily activities, weighted by their response share s_k. We evaluate $MRS_{k=1}$ at the median annual gross household income in the UK during our observation period, i.e. from 2010 to 2017, per minute. All income equivalents are standardised to exactly 60 minutes.[29] Equation 4 shows this calculation:

[28] We standardise the VOT for each activity to exactly 60 minutes for comparability with the literature.

[29] When standardising to 60 minutes, we implicitly assume a linear relationship between the hedonic experiences of activities and their durations.

$$
\begin{aligned}
VOT_{k=1} &= (MRS_{k=1} - \sum_{k=2}^{42} MRS_k \times s_k) \times Income_{UK} \times 60 \\
&= (\frac{\frac{\partial y_{it}}{\partial Waiting_{it}}}{\frac{\partial y_{it}}{\partial Income_i}} - \sum_{k=2}^{42} \frac{\frac{\partial y_{it}}{\partial A_{it,k}}}{\frac{\partial y_{it}}{\partial Income_i}} \times s_k) \times Income_{UK} \times 60 \\
&= (\frac{-3.62}{0.009} - \frac{2.49}{0.009}) \times 0.0003 \times 60 \\
&= -12.2
\end{aligned} \tag{4}
$$

where $\partial y / \partial Waiting_{it}$ is our coefficient for *waiting or queueing* (i.e. $\delta = -3.6$) obtained from Equation 2; $\partial y / \partial Income_i$ is our coefficient for log annual gross household income (i.e. 0.9) obtained from an auxiliary regression which we discuss in Section 5.2; $\partial y / \partial A_{it,k}$ are our coefficients for the $k = \{2, 3, 4, ...42\}$ other daily activities, likewise obtained from Equation 2; s_k is the response share of each activity (i.e. 2.3% for the activity *waiting of queueing*), and $Income_{UK}$ is the median annual gross household income, which was about £18,200 (\$22,750) (Office for National Statistics, 2020), adjusted to minutes.

An important feature of our method is that activities are, at the time of reporting, *duration-less*. This is an advantage: when randomly messaged by the app, respondents are not required to recall exactly how long they have been engaged in each activity (as opposed to the day-reconstruction method (cf. Kahneman et al., 2004), which may be taxing and 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 activity. Yet, to obtain $VOT_{k=1}$, we need to lend $\partial y / \partial Waiting_{it}$ a temporal dimension. We do this by adjusting income to minutes. Noting that a 1% increase in median annual gross household income is £182, this gives us an income of £182/365/24/60 = 0.0003 per minute.

4.2 VOT for 41 Other Daily Activities

Next, we calculate the VOT for each of the 41 other daily activities, in the same way as in Equation 4. Table 2 shows our results.

Table 2 about here

When it comes to enjoyable activities, we find that spending 60 minutes in the activity *sports, running, exercise* as opposed to spending them doing something else is worth £11.7 ($14.6), 60 minutes in the activity *theatre, dance, concert* £11.2 ($14), and 60 minutes in the activity *exhibition, museum, library* £8.1 ($10.1). On the contrary, spending 60 minutes in the activity *working or studying* or *commuting or travelling* is worth £−8.4 (−$10.5), spending one hour to provide care or help for adults is worth £−12.6 (−$15.6), one hour being sick in bed even £−46.4 (−$58). Again, the negative sign suggests that there is an opportunity cost to these activities, and that respondents may be better off (in terms of their hedonic experiences) spending their time doing something else. They would need to be compensated by these amounts to achieve the same level of happiness if they were not engaged in these activities.

4.3 VOT for Waiting in 41 Other Daily Activities

Finally, we look at interactions. We are particularly interested in the interaction between *waiting or queueing*, i.e. $A_{it,k=1}$, and *commuting or travelling*, i.e. $A_{it,k=4}$, to estimate the VOT for potential time savings in commuting, which we denote as $VOT_{k=1,4}$. This estimate can be compared to studies in transport economics that look at reductions in travel or waiting time during commuting. We find that spending 60 minutes in the activity *waiting or queueing* during *commuting or travelling* as opposed to spending them doing something else is worth £−17.2 ($\$-21.5$) – less than each activity on its own (cf. Table 2: £−12.2 ($\$-15.3$) per hour of waiting, £−8.4 ($\$-10.5$) per hour of commuting). Put differently, there is an opportunity cost premium for waiting during commuting (e.g. due to congestion).

To obtain $VOT_{k=1,4}$, we first re-estimate Equation 2, including an interaction between *waiting or queueing* and *commuting or travelling*:

$$\begin{aligned} y_{it} = \alpha &+ \delta_1(Waiting_{it} \times Commuting_{it}) + \delta_2 Waiting_{it} + \delta_3 Commuting_{it} \\ &+ \beta' X_{it} + r + T + u_i + \epsilon_{it} \end{aligned} \tag{5}$$

where $Waiting_{it}$ and $Commuting_{it}$ are dummies that take on one if a respondent reports to be *waiting or queueing* and *commuting or travelling*, respectively, when randomly messaged by the app, and zero else. The remainder is as before.

We then calculate $VOT_{k=1,4}$ in the same way as in Equation 4, replacing $MRS_{k=1}$ with $MRS_{k=1,4}$:

$$
\begin{aligned}
VOT_{k=1,4} &= (MRS_{k=1,4} - \sum_{k=3}^{42} MRS_k \times s_k) \times Income_{UK} \times 60 \\
&= (\frac{\frac{\partial y_{it}}{\partial (Waiting_{it} \times Commuting_{it})} + \frac{\partial y_{it}}{\partial Waiting_{it}} + \frac{\partial y_{it}}{\partial Commuting_{it}}}{\frac{\partial y_{it}}{\partial Income_i}} - \sum_{k=3}^{42} \frac{\frac{\partial y_{it}}{\partial A_{it,k}}}{\frac{\partial y_{it}}{\partial Income_i}} \times s_k) \times Income_{UK} \times 60 \\
&= (\frac{-5.71}{0.009} - \frac{2.89}{0.009}) \times 0.0003 \times 60 \\
&= -17.19
\end{aligned} \tag{6}
$$

Apart from commuting, we can also look at interactions between *waiting or queueing*, i.e. $A_{it,k=1}$, and any of the remaining $k-2$ activities, i.e. $A_{it,k-2}$, to estimate the VOT for potential time savings in any of the 40 other daily activities. Table 3 shows our results.

Table 3 about here

We find that *waiting or queueing* makes *any* of the 40 other daily activities less enjoyable, the only exception is *being sick in bed*. In particular, waiting during enjoyable activities makes these activities less enjoyable, and waiting during not enjoyable activities makes these activities even less enjoyable. There is thus a clear imperative, from an individual welfare perspective, to reduce unnecessary waiting times across activities.

5 Robustness

Our VOT depends on two factors: *(i)* our estimate of the effect of being engaged in an activity on happiness when randomly messaged by the app (e.g. $Waiting_{it}$ in case of *waiting or queueing*) and *(ii)* our estimate of the effect of income on happiness (i.e. $Income_i$). In what follows, we check the robustness of each of them. We also test our intake and experience-sampling surveys for external validity, by comparing the demographic and socio-economic characteristics as well as household characteristics in the former with those in the nationally representative UK Household Longitudinal Study ("Understanding Society"), and the activities in the latter with those in the nationally representative UK Time Use Survey.

5.1 Unobservable Selection

We first look at our estimate of the effect of being engaged in an activity on happiness, using the example of *waiting or queueing*. In particular, we test the stability of our coefficient for $Waiting_{it}$, i.e. δ in Equation 2, by first estimating a parsimonious model that includes only individual fixed effects and then successively including more controls, to elicit the extent of unobservable selection (assuming that unobservables, if any, are correlated with observables).

Appendix Table A3 shows our results. Column 1 includes only individual fixed effects, whereas Column 2 adds region and time fixed effects r and T and Column 3 time-varying experience-sampling controls X_{it}, including 41 other activities in A_{it}, seven types of company in C_{it}, three places in P_{it} and three locations in L_{it}, and meteorological conditions in M_{it}.

As seen, our coefficient for $Waiting_{it}$ remains stable, being bound between -3.1 in our model without experience-sampling controls (Column 2) and -3.6 in our full model (Column 3). It varies by less than 10%, suggesting that unobservable selection (e.g. due to omitted variables) is, if anything, only a minor issue.

5.2 Income

Next, we look at our estimate of the effect of income on happiness. Our coefficient for log annual gross household income (i.e. 0.9) comes from an auxiliary regression using our own data. In particular, we regress happiness on log annual gross household income, equivalised, from all sources using the same model as in Equation 2, with two exceptions: first, we include an additional set of time-invariant individual-level controls (i.e. age, marital status, health, and whether there are children in the household). Second, we exclude individual fixed effects. This is because respondents are asked about income only once (i.e. in the intake survey, before being asking about their momentary feelings and activities, to avoid priming).[30]

Appendix Table A4 shows our results. Column 1 includes no controls, whereas Columns 2 to 4 successively add region and time fixed effects r and T (Column 2); time-varying experience-sampling controls X_{it}, including activities in A_{it}, company in C_{it}, places in P_{it} and locations in L_{it}, and meteorological conditions in M_{it} (Column 3); and time-invariant individual-level controls in X_i (Column 4). Moreover, Column 5 replaces equivalised with non-equivalised income. Finally, Column 6 uses a filtered fixed-effects model, an approach that estimates individual fixed effects alongside time-invariant individual-level controls in a two-step procedure (cf. Pesharan and Zhou, 2016). As seen, our coefficient for $Income_i$ remains stable and robust to various parametrisations and specifications, being bound between 1.4 and 0.9, with 0.9 for equivalised income in our full model (Column 4) as our preferred coefficient.

Appendix Table A5 compares our coefficients (equivalised in Columns 1a and 1b as well as non-equivalised in Columns 2a and 2b) with selected estimates from the literature.[31] To our knowledge, the only directly comparable study to ours in terms of data and methods is Killingsworth (2021): like us, the author conducts an experience-sampling study ("Track Your Happiness") in the US, reporting a raw correlation between happiness and log annual gross household income from all sources of 1.1 in a restricted sample of employed, working-age US adults with a minimum annual income of USD $10,000$ (Column 3a), reducing to 0.7 when controlling for age, gender, marital status, and education (Column 3b). The raw correlation for an unrestricted sample is 0.9 (Column 4a), a partial correlation for that sample is not reported.[32] In sum, the only directly comparable

[30] Our measure of annual gross household income is categorical. We take the midpoint in each of the twelve categories and equivalise the resulting household income, by dividing it by the square root of the household size.

[31] While several studies attempt to estimate the effect of income on life satisfaction (i.e. a global, evaluative measure of wellbeing) (cf. Stevenson et al., 2008; Kahneman and Deaton, 2010; Sacks et al., 2010; Clark et al., 2018; De Neve et al., 2018; Lindqvist et al., 2020), few to none estimate the effect of income on happiness (i.e. a momentary, experiential measure) due to a lack of data on momentary experiences). Kahneman and Deaton (2010) compare effects between life satisfaction and happiness, but their measure of happiness is captured retrospectively by surveys, asking respondents to reflect about their happiness on the previous day, which may not constitute a genuine, in-the-moment experience.

[32] While Killingsworth (2021)'s measure of household income is similar to ours (it has slightly more categories to capture high-income individuals), the measure of happiness is slightly different. In particular, it asks respondents: "How do you feel right now?", with answers ranging from "Very bad" to "Very good".

study to ours points towards a coefficient for income that is similar to ours.

5.3 External Validity

Finally, we test our data for external validity with respect to the UK general population, by comparing the demographic and socio-economic characteristics as well as household characteristics in our intake survey with those in the nationally representative UK Household Longitudinal Study ("Understanding Society"), and the activities in our experience-sampling survey with those in the nationally representative UK Time Use Survey. For each comparison, we generate variables in the external data that are as similar as possible to ours, and then calculate normalised differences in means between our variables and those in the external data. Contrary to simple differences, normalised differences are scale-free, i.e. independent of sample size, and hence more informative about the degree of covariate imbalance, if any, between large samples cf. (Imbens and Rubin, 2015). This may be relevant in our case, as our intake survey has $30,936$ unique respondents (Understanding Society: $77,496$) and our experience-sampling survey a total of $2,235,733$ responses (UK Time Use Survey: $16,533$). To maximise comparability, we restrict Understanding Society to Wave 2 (i.e. the years 2010 to 2011, when most respondents selected into our study) and use cross-sectional weights to achieve representativeness. The UK Time Use Survey is available for the years 2014 and 2015 only.

Appendix Table A6 shows means and standard deviations for demographic and socio-economic characteristics as well as household characteristics by sample and normalised differences in means between them. As seen, only few normalised differences exceed 0.25, which Imbens and Wooldridge (2009) suggest as a threshold above which covariates are considered unbalanced. Perhaps unsurprisingly, respondents in our sample tend to be younger, less likely to be married, more likely to be employed or self-employed, and less likely to be retired, compared to the UK general population. They are, however, relatively similar when it comes to gender, self-assessed health, annual gross household income, and household composition, including the number of adults and children in the household. They are also relatively similar with respect to their geographical distribution across the UK.

Similarly, Appendix Table A7a shows means and standard deviations for activities on weekdays by sample and normalised differences in means between them. Appendix Table A7a shows the same for activities on weekends and holidays.[33] Here, none of the normalised differences exceed 0.25. The similarity between activities reported in our data and those reported in the external data also suggests that selection into the reporting of activities, i.e. $R(Waiting_{it})$, which may yield potentially biased response shares s, is, if anything, only a minor issue.

Taken together, both visual inspection and normalised differences suggest that our data score high in terms of external validity with respect to the UK general population.

6 Discussion

We proposed an alternative method to stated or revealed preferences for valuing time and associated time savings: *experiential valuation* based on experience-sampling. Unlike stated or revealed preferences, our method does not rely on choice architecture, nor does it require individuals to predict the welfare consequences of different choices. Most importantly, it allows individuals to judge for themselves what constitutes a particular use of their time and how they feel about it.

While we are the first to exploit hedonic experiences in real-time to value time (or anything), the idea behind this approach is old, going back to the early economist Francis Y. Edgeworth (1845-1926), who argued that a *hedonimeter* would eventually make it possible for economists to directly measure utility on a physiological basis. Much less ambitious, we used a smartphone app that during the years 2010 to 2017 randomly asked a panel of $30,936$ UK residents ($N = 2,235,733$) about their momentary feelings and activities as they went about their daily lives.

We used these rich panel data to estimate the VOT for 42 daily activities, by subtracting from the income equivalent of each activity the weighted average of the income equivalents of all the other activities (i.e. the counterfactual). We started with the activity *waiting or queueing* to estimate the VOT associated with potential time savings from reducing waiting time in general, and then looked at commuting and the interaction between waiting and commuting to estimate the VOT

[33] In this analysis, we need to differentiate weekdays from weekends because the UK Time Use Survey oversamples weekends.

for commuting and potential time savings in commuting. Our method, however, is more flexible than existing studies, allowing us to calculate the VOT for the remaining 40 daily activities too. Our regressions looked at within-individual variation, controlling for other activities respondents may be simultaneously engaged in, where they currently are, who they are with, meteorological conditions, and region and time fixed effects.

We arrived at a VOT of £12.2 ($15.3) per hour of waiting, £8.4 ($10.5) per hour of commuting, and £17.2 ($21.5) per hour of waiting during commuting (e.g. due to traffic). Put differently, a person spending 60 minutes in the activity *commuting or travelling* as opposed to spending them doing something else would need to be compensated 8.4 ($10.5) to achieve the same level of happiness if they were not commuting, and even £17.2 ($21.5) if they were waiting during their commute (e.g. in traffic or due to a delay). These figures could be used in cost-benefit analyses to quantify the benefits associated with investments into time-saving infrastructure. As it turns out, they also compare well to estimates from revealed preferences, suggesting that using hedonic experiences leads to similar (though not identical) results as observed behaviour.

Our method could complement using accounts of self-reported life satisfaction for non-market or intangible valuation, an approach that has become accepted in the literature (cf. van Praag and Baarsma, 2005; Luechinger, 2009; Levinson, 2012; Krekel and Zerrahn, 2017; Dolan et al., 2019) and that is now part of official UK Treasury guidelines for policy appraisal and evaluation (HM Treasury, 2021b,a). In particular, hedonic experiences in real-time could be used to value non-market goods or intangibles that are too granular to be captured by accounts of self-reported life satisfaction, such as infrequent time spent in various activities (e.g. cultural activities) or places (e.g. historical sites), but that are nevertheless of policy interest as they provide public value. For example, spending 60 minutes in the activity *sports, running, exercise* as opposed to spending them doing something else can be valued at £11.7 ($14.6), 60 minutes in the activity *theatre, dance,* *concert* at £11.2 (\$14), and 60 minutes in the activity *exhibition, museum, library* at £8.1 (\$10.1).[34]

Our study has several limitations. When it comes to internal validity, we were not able to claim causality for our coefficients, which would have required an exogenous source of variation. In fact, to estimate the VOT for 42 daily activities, we would have to set up 42 quasi-experiments with 42 (potentially different, activity-specific) sources of variation, which is a difficult task. At the same time, focusing on one activity may help with causality but may come at the cost of generalisability. Note, however, that our coefficients remain stable regardless of whether or not we include time-varying experience-sampling controls as well as spatial and temporal fixed effects, which suggests that unobservable selection may be less of a concern. When it comes to external validity, we do not have a representative sample, and respondents in our sample tend to be younger (and potentially more technologically savvy) than the UK general population. Note, however, that many other individual characteristics in our sample compare quite well with those in nationally representative longitudinal household data, and many activities in our sample with those in nationally representative time use data in the UK, which suggests that external validity is relatively high.

How people spend their time determines to a large extent how satisfied they are with their lives and how happy they are in the moment. Valuing their hedonic experiences in real-time may help putting a price tag on different uses of their time, thereby making them more relevant for policy. It has the potential to value other intangibles too.

[34] HM Treasury now allows the concept of a *Wellbeing-Adjusted Life Year (WELLBY)* as a measure of benefit, which is defined as one point of self-reported life satisfaction on a zero-to-ten scale for one individual for one year (Frijters et al., 2020; Frijters and Krekel, 2021) and which is currently valued at £$13,000$ (HM Treasury, 2021b,a). As a complement, one could think of an equivalent, experiential measure, e.g. a *Wellbeing-Adjusted Life Hour (WELLBH)*, which could be defined as one point of self-reported happiness in real-time on a zero-to-ten scale for one individual for one hour. Using our data and method, it can be valued at £20 (the marginal rate of substitution between one point of happiness and income, rescaled from a zero-to-hundred to the more conventional zero-to-ten scale and standardised to one hour, is $\pounds(1/0.0009) \times 0.0003 \times 60) = \pounds 20$. Yet, more work needs to be done to make evaluative and experiential measures of wellbeing more compatible with each other.

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Figure 1: Smartphone App – Randomisation Algorithm

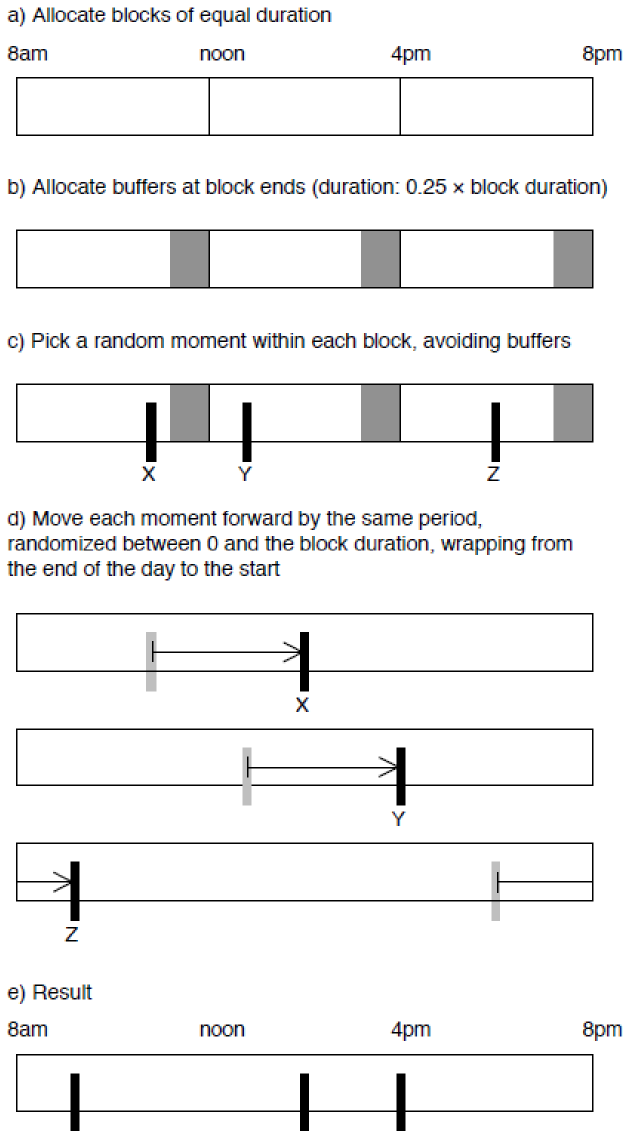

Table 1: Regression Results

	Happy (0-100) Coefficient	Standard Error	Response Share s
Waiting, Queueing	-3.62***	(0.14)	2.32%
Other Activities (A_{it})			
Working, Studying	-1.61***	(0.08)	24.98%
In Meeting, Seminar, Class	0.30***	(0.11)	2.83%
Commuting, Travelling	-1.86***	(0.10)	8.98%
Cooking, Preparing Food	2.24***	(0.08)	4.31%
Housework, Chores, DIY	-0.53***	(0.08)	5.19%
Shopping, Running Errands	0.71***	(0.09)	3.01%
Admin, Finances, Organising	-1.27***	(0.12)	3.92%
Childcare, Playing With Children	2.77***	(0.14)	4.45%
Petcare, Playing With Pets	3.19***	(0.17)	1.88%
Care or Help for Adults	-3.85***	(0.62)	0.54%
Sleeping, Resting, Relaxing	0.92***	(0.07)	9.86%
Sick in Bed	-18.37***	(0.29)	1.53%
Meditating, Religious Activities	3.95***	(0.37)	0.31%
Washing, Dressing, Grooming	2.01***	(0.08)	3.68%
Talking, Chatting, Socialising	4.17***	(0.07)	14.93%
Intimacy, Making Love	12.66***	(0.26)	0.56%
Eating, Snacking	2.01***	(0.06)	9.82%
Drinking Tea or Coffee	1.39***	(0.06)	6.42%
Drinking Alcohol	3.61***	(0.09)	5.07%
Smoking	0.45**	(0.18)	1.32%
Texting, E-Mail, Social Media	0.92***	(0.08)	5.62%
Browsing the Internet	0.78***	(0.08)	5.13%
Watching TV, Film	2.28***	(0.06)	18.00%
Listening to Music	3.28***	(0.09)	6.27%
Listening to Speech or Podcast	1.75***	(0.12)	2.09%
Reading	1.93***	(0.12)	3.30%
Theatre, Dance, Concert	6.55***	(0.25)	0.33%
Exhibition, Museum, Library	5.18***	(0.25)	0.23%
Match, Sporting Event	2.37***	(0.27)	0.60%
Walking, Hiking	2.40***	(0.14)	1.48%
Sports, Running, Exercise	6.71***	(0.15)	1.25%
Gardening, Allotment	4.83***	(0.24)	0.31%
Birdwatching, Nature Watching	4.52***	(0.35)	0.16%
Computer Games, Smart Phone Games	2.59***	(0.11)	2.82%
Hunting, Fishing	3.59***	(0.97)	0.02%
Other Games, Puzzles	2.70***	(0.21)	0.40%
Gambling, Betting	1.61**	(0.64)	0.07%
Hobbies, Arts, Crafts	5.14***	(0.21)	1.03%
Singing, Performing	6.00***	(0.28)	0.40%
Something Else	-1.54***	(0.17)	1.28%
Other	-3.58***	(0.51)	3.13%
Company (C_{it})			
Spouse, Partner, Girlfriend, or Boyfriend	3.68***	(0.09)	
Children	0.45***	(0.12)	
Other Family Members	0.84***	(0.08)	
Colleagues, Classmates	-0.22*	(0.10)	
Clients, Customers	1.11***	(0.23)	
Friends	4.14***	(0.08)	
Other People You Know	-0.57***	(0.13)	
Place (P_{it})			
At Work	Reference Category		
At Home	2.80***	(0.09)	
Elsewhere	0.18*	(0.10)	
Location (L_{it})			
Indoors	Reference Category		
Outdoors	1.45***	(0.07)	
In Vehicle	-2.42***	(0.11)	
Meteorological Controls (M_{it})			
Air Temperature	Yes		
Wind Speed	Yes		
Precipitation	Yes		
Cloud Cover	Yes		
Sunshine	Yes		
Daylight	Yes		
Spatial Controls (r)			
Region Fixed Effects	Yes		
Temporal Controls (T)			
Holiday-Season Fixed Effects	Yes		
Hour-of-Day Fixed Effects	Yes		
Day-of-Week Fixed Effects	Yes		
Month Fixed Effects	Yes		
Year Fixed Effects	Yes		
Individual Fixed Effects	Yes		
Constant	Yes		
Number of Individuals	30,936		
Number of Observations	2,235,733		
Adjusted R Squared	0.44		
Adjusted R Squared Within	0.11		
F-Test	190.45		

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

Table 2: Value of Time (VOT) for 41 Daily Activities

k	Activity $A_{it,k}$	Happy (0-100) Coefficient (1)	Monetary Equivalent (£, 60 Minutes) (2)	Response Share s (3)	s-Weighted Average of Column 2 Excluding k (4)	VOT (£, 60 Minutes) (5) = (2) - (4)
1	Waiting, Queueing	-3.62	-8.26	2.32%	3.96	-12.22
2	Working, Studying	-1.61	-3.68	24.98%	4.69	-8.37
3	In Meeting, Seminar, Class	0.30	0.68	2.83%	3.75	-3.07
4	Commuting, Travelling	-1.86	-4.25	8.98%	4.15	-8.40
5	Cooking, Preparing Food	2.24	5.11	4.31%	3.55	1.56
6	Housework, Chores, DIY	-0.53	-1.21	5.19%	3.83	-5.04
7	Shopping, Running Errands	0.71	1.62	3.01%	3.72	-2.10
8	Admin, Finances, Organising	-1.27	-2.90	3.92%	3.88	-6.78
9	Childcare, Playing With Children	2.77	6.32	4.45%	3.49	2.83
10	Petcare, Playing With Pets	3.19	7.28	1.88%	3.63	3.65
11	Care or Help for Adults	-3.85	-8.79	0.54%	3.82	-12.61
12	Sleeping, Resting, Relaxing	0.92	2.10	9.86%	3.56	-1.46
13	Sick in Bed	-18.37	-41.94	1.53%	4.41	-46.35
14	Meditating, Religious Activities	3.95	9.02	0.31%	3.74	5.28
15	Washing, Dressing, Grooming	2.01	4.59	3.68%	3.60	0.99
16	Talking, Chatting, Socialising	4.17	9.52	14.93%	2.35	7.17
17	Intimacy, Making Love	12.66	28.90	0.56%	3.61	25.29
18	Eating, Snacking	2.01	4.59	9.82%	3.32	1.27
19	Drinking Tea or Coffee	1.39	3.17	6.42%	3.57	-0.40
20	Drinking Alcohol	3.61	8.24	5.07%	3.35	4.89
21	Smoking	0.45	1.03	1.32%	3.76	-2.73
22	Texting, E-Mail, Social Media	0.92	2.10	5.62%	3.65	-1.55
23	Browsing the Internet	0.78	1.78	5.13%	3.68	-1.90
24	Watching TV, Film	2.28	5.21	18.00%	2.83	2.38
25	Listening to Music	3.28	7.49	6.27%	3.30	4.19
26	Listening to Speech or Podcast	1.75	4.00	2.09%	3.69	0.31
27	Reading	1.93	4.41	3.30%	3.63	0.78
28	Theatre, Dance, Concert	6.55	14.95	0.33%	3.72	11.23
29	Exhibition, Museum, Library	5.18	11.83	0.23%	3.74	8.09
30	Match, Sporting Event	2.37	5.41	0.60%	3.74	1.67
31	Walking, Hiking	2.40	5.48	1.48%	3.69	1.79
32	Sports, Running, Exercise	6.71	15.32	1.25%	3.58	11.74
33	Gardening, Allotment	4.83	11.03	0.31%	3.74	7.29
34	Birdwatching, Nature Watching	4.52	10.32	0.16%	3.75	6.57
35	Computer Games, Smart Phone Games	2.59	5.91	2.82%	3.60	2.31
36	Hunting, Fishing	3.59	8.20	0.02%	3.77	4.43
37	Other Games, Puzzles	2.70	6.16	0.40%	3.75	2.41
38	Gambling, Betting	1.61	3.68	0.07%	3.77	-0.09
39	Hobbies, Arts, Crafts	5.14	11.74	1.03%	3.65	8.09
40	Singing, Performing	6.00	13.70	0.40%	3.72	9.98
41	Something Else	-1.54	-3.52	1.28%	3.82	-7.34
42	Other	-3.58	-8.17	3.13%	4.03	-12.20

Table 3: Value of Time (VOT) for Waiting in 40 Daily Activities

k	Activity $A_{it,k}$	Happy (0-100) Coefficients $A_{it,k}$ (1)	$Waiting_{it}$ (2)	$A_{it,k} \times Waiting_{it}$ (3)	(4) = (1) + (2) + (3)	Monetary Equivalent (£, 60 Minutes) of Column 4 (5)	s-Weighted Average of Table 2 Column 2 Excluding k (6)	VOT (£, 60 Minutes) (7) = (5) - (6)
2	Working, Studying	-1.68	-4.43	1.33	-4.77	-10.90	4.69	-15.59
3	In Meeting, Seminar, Class	0.27	-4.43	-0.53	-4.69	-10.72	3.75	-14.47
4	Commuting, Travelling	-1.97	-4.43	0.69	-5.71	-13.04	4.15	-17.19
5	Cooking, Preparing Food	2.20	-4.43	0.75	-1.48	-3.37	3.55	-6.92
6	Housework, Chores, DIY	-0.58	-4.43	0.98	-4.04	-9.21	3.83	-13.05
7	Shopping, Running Errands	0.61	-4.43	0.71	-3.12	-7.11	3.72	-10.83
8	Admin, Finances, Organising	-1.33	-4.43	1.06	-4.70	-10.73	3.88	-14.61
9	Childcare, Playing With Children	2.74	-4.43	0.21	-1.48	-3.37	3.49	-6.86
10	Petcare, Playing With Pets	3.19	-4.43	-0.94	-2.18	-4.97	3.63	-8.61
11	Care or Help for Adults	-4.10	-4.43	0.34	-8.20	-18.71	3.82	-22.53
12	Sleeping, Resting, Relaxing	0.87	-4.43	1.78	-1.78	-4.07	3.56	-7.64
13	Sick in Bed	-18.57	-4.43	10.85	-12.14	-27.72	4.41	-32.13
14	Meditating, Religious Activities	3.98	-4.43	-3.45	-3.90	-8.90	3.74	-12.64
15	Washing, Dressing, Grooming	1.94	-4.43	0.97	-1.52	-3.47	3.60	-7.07
16	Talking, Chatting, Socialising	4.12	-4.43	1.56	1.25	2.85	2.35	0.50
17	Intimacy, Making Love	12.66	-4.43	-3.94	4.29	9.81	3.61	6.20
18	Eating, Snacking	1.98	-4.43	0.83	-1.62	-3.70	3.32	-7.02
19	Drinking Tea or Coffee	1.37	-4.43	0.44	-2.62	-5.98	3.57	-9.55
20	Drinking Alcohol	3.59	-4.43	0.88	0.04	0.10	3.35	-3.26
21	Smoking	0.41	-4.43	1.76	-2.26	-5.16	3.76	-8.92
22	Texting, E-Mail, Social Media	0.88	-4.43	0.65	-2.90	-6.62	3.65	-10.27
23	Browsing the Internet	0.74	-4.43	0.85	-2.83	-6.46	3.68	-10.14
24	Watching TV, Film	2.26	-4.43	-0.67	-2.84	-6.48	2.83	-9.31
25	Listening to Music	3.28	-4.43	-0.29	-1.43	-3.27	3.30	-6.58
26	Listening to Speech or Podcast	1.71	-4.43	0.40	-2.31	-5.28	3.69	-8.97
27	Reading	1.90	-4.43	-0.06	-2.59	-5.92	3.63	-9.54
28	Theatre, Dance, Concert	6.47	-4.43	1.01	3.05	6.95	3.72	3.23
29	Exhibition, Museum, Library	5.20	-4.43	-0.85	-0.12	-0.27	3.74	-4.01
30	Match, Sporting Event	2.30	-4.43	0.56	-1.56	-3.57	3.74	-7.30
31	Walking, Hiking	2.38	-4.43	-2.34	-4.39	-10.02	3.69	-13.71
32	Sports, Running, Exercise	6.66	-4.43	-0.42	1.80	4.12	3.58	0.54
33	Gardening, Allotment	4.77	-4.43	-0.44	-0.10	-0.22	3.74	-3.95
34	Birdwatching, Nature Watching	4.41	-4.43	1.91	1.89	4.31	3.75	0.56
35	Computer Games, Smart Phone Games	2.59	-4.43	-1.62	-3.47	-7.91	3.60	-11.52
36	Hunting, Fishing	3.54	-4.43	-1.02	-1.91	-4.37	3.77	-8.14
37	Other Games, Puzzles	2.71	-4.43	-1.30	-3.02	-6.89	3.75	-10.64
38	Gambling, Betting	1.71	-4.43	-4.57	-7.29	-16.64	3.77	-20.41
39	Hobbies, Arts, Crafts	5.09	-4.43	0.95	1.61	3.68	3.65	0.03
40	Singing, Performing	6.01	-4.43	-3.48	-1.90	-4.34	3.72	-8.06
41	Something Else	-1.51	-4.43	-3.97	-9.91	-22.62	3.82	-26.43
42	Other	-3.63	-4.43	-0.07	-8.13	-18.56	4.03	-22.59

Appendix

Figure A1: Smartphone App – User Interface

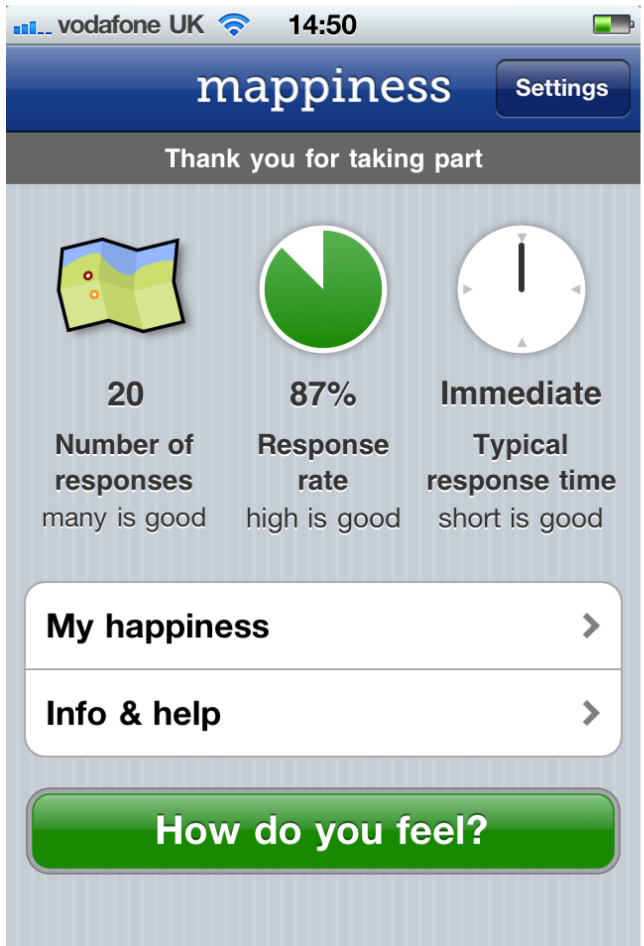

Figure A2: Smartphone App – Experience-Sampling Survey

Figure A3: Smartphone App – Personalised Feedback

Figure A4: Smartphone App – Settings

Table A1: Summary Statistics – Intake Survey

	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
Age					
… 18 to 24	0.21	0.41	0	1	30,936
… 25 to 34	0.41	0.49	0	1	30,936
… 35 to 44	0.25	0.43	0	1	30,936
… 45 to 54	0.10	0.30	0	1	30,936
… 55 to 64	0.03	0.17	0	1	30,936
… 65 to 74	0.00	0.06	0	1	30,936
… 75 or Over	0.00	0.02	0	1	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
Marital Status					
… 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					
… 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					
… None	0.71	0.45	0	1	30,936
… 1	0.13	0.34	0	1	30,936
… 2	0.11	0.32	0	1	30,936
… 3	0.03	0.17	0	1	30,936
… 4 or More	0.01	0.09	0	1	30,936
Region					
… North East	0.03	0.17	0	1	30,936
… North West	0.08	0.27	0	1	30,936
… Yorkshire and the Humber	0.06	0.23	0	1	30,936
… East Midlands	0.05	0.22	0	1	30,936
… West Midlands	0.06	0.23	0	1	30,936
… East of England	0.07	0.26	0	1	30,936
… London	0.24	0.43	0	1	30,936
… South East	0.15	0.35	0	1	30,936
… South West	0.07	0.26	0	1	30,936
… Northern Ireland	0.01	0.11	0	1	30,936
… Scotland	0.06	0.23	0	1	30,936
… Wales	0.03	0.18	0	1	30,936
… Not Reported	0.09	0.28	0	1	30,936

Table A2: Summary Statistics – Experience-Sampling Survey

	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
Activities					
Waiting, Queueing	0.02	0.15	0	1	2,235,733
Working, Studying	0.25	0.43	0	1	2,235,733
In Meeting, Seminar, Class	0.03	0.17	0	1	2,235,733
Commuting, Travelling	0.09	0.29	0	1	2,235,733
Cooking, Preparing Food	0.04	0.20	0	1	2,235,733
Housework, Chores, DIY	0.05	0.22	0	1	2,235,733
Shopping, Running Errands	0.03	0.17	0	1	2,235,733
Admin, Finances, Organising	0.04	0.19	0	1	2,235,733
Childcare, Playing With Children	0.04	0.21	0	1	2,235,733
Petcare, Playing With Pets	0.02	0.14	0	1	2,235,733
Care or Help for Adults	0.01	0.07	0	1	2,235,733
Sleeping, Resting, Relaxing	0.10	0.30	0	1	2,235,733
Sick in Bed	0.02	0.12	0	1	2,235,733
Meditating, Religious Activities	<0.00	0.06	0	1	2,235,733
Washing, Dressing, Grooming	0.04	0.19	0	1	2,235,733
Talking, Chatting, Socialising	0.01	0.36	0	1	2,235,733
Intimacy, Making Love	0.01	0.07	0	1	2,235,733
Eating, Snacking	0.10	0.30	0	1	2,235,733
Drinking Tea or Coffee	0.06	0.25	0	1	2,235,733
Drinking Alcohol	0.05	0.22	0	1	2,235,733
Smoking	0.01	0.11	0	1	2,235,733
Texting, E-Mail, Social Media	0.06	0.23	0	1	2,235,733
Browsing the Internet	0.05	0.22	0	1	2,235,733
Watching TV, Film	0.18	0.38	0	1	2,235,733
Listening to Music	0.06	0.24	0	1	2,235,733
Listening to Speech or Podcast	0.02	0.14	0	1	2,235,733
Reading	0.03	0.18	0	1	2,235,733
Theatre, Dance, Concert	<0.00	0.06	0	1	2,235,733
Exhibition, Museum, Library	<0.00	0.05	0	1	2,235,733
Match, Sporting Event	0.01	0.08	0	1	2,235,733
Walking, Hiking	0.01	0.12	0	1	2,235,733
Sports, Running, Exercise	0.01	0.11	0	1	2,235,733
Gardening, Allotment	<0.00	0.06	0	1	2,235,733
Birdwatching, Nature Watching	<0.00	0.04	0	1	2,235,733
Computer Games, Smart Phone Games	0.03	0.17	0	1	2,235,733
Hunting, Fishing	<0.00	0.01	0	1	2,235,733
Other Games, Puzzles	<0.00	0.06	0	1	2,235,733
Gambling, Betting	<0.00	0.03	0	1	2,235,733
Hobbies, Arts, Crafts	0.01	0.10	0	1	2,235,733
Singing, Performing	<0.00	0.06	0	1	2,235,733
Something Else	0.01	0.11	0	1	2,235,733
Other	0.03	0.17	0	1	2,235,733
Company					
Spouse, Partner, Girlfriend, or Boyfriend	0.24	0.43	0	1	2,235,733
Children	0.11	0.31	0	1	2,235,733
Other Family Members	0.07	0.26	0	1	2,235,733
Colleagues, Classmates	0.17	0.38	0	1	2,235,733
Clients, Customers	0.02	0.12	0	1	2,235,733
Friends	0.09	0.28	0	1	2,235,733
Other People You Know	0.02	0.12	0	1	2,235,733
Alone	0.04	0.50	0	1	2,235,733
Place					
At Work	0.24	0.42	0	1	2,235,733
At Home	0.51	0.50	0	1	2,235,733
Elsewhere	0.25	0.44	0	1	2,235,733
Location					
Indoors	0.84	0.36	0	1	2,235,733
Outdoors	0.08	0.28	0	1	2,235,733
In Vehicle	0.07	0.26	0	1	2,235,733

Table A3: Stability of Activity Estimate – Waiting or Queueing

	Happy (0-100)		
	(1)	(2)	(3)
Waiting, Queueing	-3.31***	-3.11***	-3.62***
	(0.16)	(0.14)	(0.14)
Experience-Sampling Controls (X_{it})			
Other Activities	No	No	Yes
Company	No	No	Yes
Place	No	No	Yes
Location	No	No	Yes
Meteorological Conditions	No	No	Yes
Spatial Controls (r)			
Region Fixed Effects	No	Yes	Yes
Temporal Controls (T)			
Holiday-Season Fixed Effects	No	Yes	Yes
Hour-of-Day Fixed Effects	No	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes
Month Fixed Effects	No	Yes	Yes
Year Fixed Effects	No	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Number of Individuals	30,936	30,936	30,936
Number of Observations	2,235,733	2,235,733	2,235,733
Adjusted R Squared	0.35	0.38	0.44
Adjusted R Squared Within	0.00	0.02	0.11
F-Test	419.87	87.14	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 A4: Stability of Income Estimate

	Happy (0-100)					
	OLS					FE Filtered
	(1)	(2)	(3)	(4)	(5)	(6)
Log Equivalised Annual Gross Household Income	1.38***	1.17***	1.17***	0.91***		0.94***
	(0.35)	(0.19)	(0.19)	(0.19)		(0.09)
Log Annual Gross Household Income					0.91***	
					(0.20)	
Additional Individual-Level Controls (X_i)						
Age	No	No	No	Yes	Yes	Yes
Marital Status	No	No	No	Yes	Yes	Yes
Children	No	No	No	Yes	Yes	Yes
Health	No	No	No	Yes	Yes	Yes
Experience-Sampling Controls (X_{it})						
Other Activities	No	No	Yes	Yes	Yes	Yes
Company	No	No	Yes	Yes	Yes	Yes
Place	No	No	Yes	Yes	Yes	Yes
Location	No	No	Yes	Yes	Yes	Yes
Meteorological Conditions	No	No	Yes	Yes	Yes	Yes
Spatial Controls (r)						
Region Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Temporal Controls (T)						
Holiday-Season Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Hour-of-Day Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	No	No	No	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Number of Individuals	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
Adjusted R Squared	0.00	0.13	0.13	0.21	0.21	-
Adjusted R Squared Within	0.00	0.02	0.02	0.12	0.12	-
F-Test	15.94	63.01	58.55	140.31	140.26	-

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

Table A5: Comparison of Income Estimate

	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 Annual Gross 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	-

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

Table A5 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.

Table A6: External Validity of Intake Survey – Comparison to UK Household Longitudinal Study

	"Mappiness" Study		"Understanding Society" (Wave 2, Years 2010 to 2011)			
	Mean	Standard Deviation	Mean	Standard Deviation	Normalised Difference	> 0.25?
Age						
… 18 to 24	0.21	0.41	0.11	0.31	0.20	No
… 25 to 34	0.41	0.49	0.16	0.37	0.40	Yes
… 35 to 44	0.25	0.43	0.18	0.38	0.13	No
… 45 to 54	0.10	0.30	0.18	0.39	-0.17	No
… 55 to 64	0.03	0.17	0.16	0.36	-0.32	Yes
… 65 to 74	<0.00	0.06	0.12	0.32	-0.35	Yes
… 75 or Over	<0.00	0.02	0.10	0.30	-0.33	Yes
Gender						
… Male	0.51	0.50	0.48	0.50	0.04	No
… Female	0.49	0.50	0.52	0.50	-0.04	No
Relationship Status						
… Not in Relationship	0.20	0.40	N/A	N/A	N/A	N/A
… In Relationship	0.80	0.40	N/A	N/A	N/A	N/A
Marital Status						
… Never Married	0.60	0.49	0.24	0.43	0.56	Yes
… Married and Living With Spouse	0.32	0.47	0.62	0.49	-0.44	Yes
… Married but Separated	0.03	0.16	0.02	0.12	0.07	No
… Divorced	0.05	0.21	0.06	0.24	-0.03	No
… Widowed	<0.00	0.06	0.07	0.25	-0.24	No
Self-Assessed Health						
… Excellent Health	0.14	0.35	0.16	0.37	-0.05	No
… Very Good Health	0.42	0.49	0.34	0.47	0.12	No
… Good Health	0.32	0.47	0.28	0.45	0.06	No
… Fair Health	0.09	0.29	0.15	0.36	-0.13	No
… Poor Health	0.02	0.13	0.06	0.25	-0.16	No
Employment Status						
… In Full-Time Education	0.12	0.32	0.07	0.25	0.13	No
… Employed or Self-Employed	0.80	0.40	0.55	0.50	0.39	Yes
… Unemployed and Looking	0.03	0.16	0.05	0.23	-0.09	No
… Long-Term Sick or Disabled	0.01	0.10	0.03	0.18	-0.12	No
… Looking After Family or Home	0.02	0.15	0.05	0.22	-0.12	No
… Retired	0.01	0.09	0.23	0.42	-0.52	Yes
… Other	0.01	0.12	0.01	0.09	0.01	No
Annual Gross Household Income						
… Under £8,000	0.06	0.23	0.04	0.18	0.08	No
… £8,000 to £11,999	0.03	0.17	0.06	0.23	-0.10	No
… £12,000 to £15,999	0.04	0.20	0.08	0.27	-0.11	No
… £16,000 to £19,999	0.04	0.21	0.08	0.27	-0.12	No
… £20,000 to £23,999	0.06	0.23	0.07	0.26	-0.04	No
… £24,000 to £31,999	0.11	0.31	0.14	0.35	-0.06	No
… £32,000 to £39,999	0.11	0.32	0.12	0.32	-0.02	No
… £40,000 to £55,999	0.19	0.39	0.18	0.38	0.02	No
… £56,000 to £71,999	0.14	0.35	0.11	0.31	0.07	No
… £72,000 to £95,999	0.10	0.30	0.07	0.26	0.06	No
… £96,000 or More	0.12	0.32	0.06	0.24	0.15	No
Number of Adults in Household						
… 1	0.20	0.40	0.18	0.38	0.04	No
… 2	0.55	0.50	0.52	0.50	0.05	No
… 3	0.13	0.34	0.18	0.38	-0.09	No
… 4 or More	0.12	0.32	0.12	0.33	-0.01	No
Number of Children in Household						
… None	0.71	0.45	0.69	0.46	0.03	No
… 1	0.13	0.34	0.15	0.36	-0.04	No
… 2	0.11	0.32	0.11	0.32	-0.01	No
… 3	0.03	0.17	0.03	0.18	-0.01	No
… 4 or More	0.01	0.09	0.01	0.11	-0.01	No
Region						
… North East	0.03	0.17	0.04	0.20	-0.04	No
… North West	0.08	0.27	0.11	0.32	-0.08	No
… Yorkshire and the Humber	0.06	0.23	0.08	0.28	-0.07	No
… East Midlands	0.05	0.22	0.07	0.26	-0.07	No
… West Midlands	0.06	0.23	0.09	0.28	-0.08	No
… East of England	0.07	0.26	0.10	0.29	-0.07	No
… London	0.24	0.43	0.12	0.32	0.23	No
… South East	0.15	0.35	0.14	0.34	0.03	No
… South West	0.07	0.26	0.09	0.28	-0.04	No
… Northern Ireland	0.01	0.11	0.03	0.17	-0.09	No
… Scotland	0.06	0.23	0.08	0.28	-0.07	No
… Wales	0.03	0.18	0.05	0.22	-0.07	No
… Not Reported	0.09	0.28	¡0.00	0.03	0.32	No
N	30,936	-	77,496	-	-	-

Table A7a: External Validity of Experience-Sampling Survey – Comparison to UK Time Use Survey (Week Days)

Week Days (i.e. Monday to Friday)	"Mappiness" Study		UK Time Use Survey (Years 2014 and 2015)			
	Mean	Standard Deviation	Mean	Standard Deviation	Normalised Differences	> 0.25?
Activities						
Waiting, Queueing	0.02	0.15	N/A	N/A	N/A	N/A
Working, Studying	0.33	0.47	0.26	0.30	0.12	No
In Meeting, Seminar, Class	0.04	0.19	0.01	0.06	0.15	No
Commuting, Travelling	0.10	0.30	0.09	0.10	0.02	No
Cooking, Preparing Food	0.04	0.19	0.06	0.07	-0.10	No
Housework, Chores, DIY	0.04	0.20	0.06	0.09	-0.07	No
Shopping, Running Errands	0.03	0.16	0.04	0.07	-0.10	No
Admin, Finances, Organising	0.04	0.21	<0.00	0.01	0.21	No
Childcare, Playing With Children	0.04	0.19	0.03	0.09	0.04	No
Petcare, Playing With Pets	0.02	0.13	0.01	0.04	0.02	No
Care or Help for Adults	0.01	0.07	<0.00	0.02	0.04	No
Sleeping, Resting, Relaxing	0.08	0.26	0.07	0.11	0.01	No
Sick in Bed	0.02	0.12	<0.00	0.03	0.11	No
Meditating, Religious Activities	<0.00	0.05	<0.00	0.02	-0.01	No
Washing, Dressing, Grooming	0.03	0.18	0.04	0.05	-0.05	No
Talking, Chatting, Socialising	0.13	0.33	0.11	0.14	0.04	No
Intimacy, Making Love	<0.00	0.06	N/A	N/A	N/A	N/A
Eating, Snacking	0.09	0.29	0.10	0.08	-0.05	No
Drinking Tea or Coffee	0.06	0.24	N/A	N/A	N/A	N/A
Drinking Alcohol	0.04	0.20	N/A	N/A	N/A	N/A
Smoking	0.01	0.11	N/A	N/A	N/A	N/A
Texting, E-Mail, Social Media	0.06	0.23	N/A	N/A	N/A	N/A
Browsing the Internet	0.05	0.22	0.04	0.07	0.06	No
Watching TV, Film	0.15	0.36	0.16	0.15	-0.03	No
Listening to Music	0.06	0.24	0.04	0.10	0.07	No
Listening to Speech or Podcast	0.02	0.14	N/A	N/A	N/A	N/A
Reading	0.03	0.17	0.02	0.06	0.03	No
Theatre, Dance, Concert	<0.00	0.05	<0.00	0.01	0.03	No
Exhibition, Museum, Library	<0.00	0.04	<0.00	0.01	0.02	No
Match, Sporting Event	<0.00	0.06	<0.00	0.01	0.05	No
Walking, Hiking	0.01	0.11	0.01	0.02	0.06	No
Sports, Running, Exercise	0.01	0.11	0.01	0.05	-0.01	No
Gardening, Allotment	<0.00	0.04	0.01	0.04	-0.12	No
Birdwatching, Nature Watching	<0.00	0.03	<0.00	0.03	-0.05	No
Computer Games, Smart Phone Games	0.03	0.16	0.01	0.04	0.10	No
Hunting, Fishing	<0.00	0.01	<0.00	0.02	-0.02	No
Other Games, Puzzles	<0.00	0.06	0.01	0.03	-0.06	No
Gambling, Betting	<0.00	0.02	<0.00	0.01	-0.01	No
Hobbies, Arts, Crafts	0.01	0.09	0.01	0.03	0.03	No
Singing, Performing	<0.00	0.06	N/A	N/A	N/A	N/A
Something Else	0.01	0.11	N/A	N/A	N/A	N/A
Other	0.03	0.17	N/A	N/A	N/A	N/A
Company						
Spouse, Partner, Girlfriend, or Boyfriend	0.17	0.38	0.22	0.27	-0.10	No
Children	0.08	0.28	0.07	0.20	0.04	No
Other Family Members	0.05	0.23	0.11	0.20	-0.18	No
Colleagues, Classmates	0.23	0.42	0.25	0.27	-0.04	No
Clients, Customers	0.02	0.14	N/A	N/A	N/A	N/A
Friends	0.08	0.26	N/A	N/A	N/A	N/A
Other People You Know	0.01	0.12	N/A	N/A	N/A	N/A
Alone	0.45	0.50	0.32	0.28	0.23	No
Place						
At Work	0.32	0.47	0.21	0.28	0.20	No
At Home	0.45	0.50	0.53	0.30	-0.13	No
Elsewhere	0.23	0.42	0.26	0.30	-0.06	No
Location						
Indoors	0.85	0.36	0.81	0.20	0.09	No
Outdoors	0.08	0.27	0.03	0.06	0.16	No
In Vehicle	0.07	0.26	0.08	0.11	-0.01	No
N	1,567,160	-	8,288	-	-	-

Table A7b: External Validity of Experience-Sampling Survey – Comparison to UK Time Use Survey (Weekends and Holidays)

Weekends (i.e. Saturday and Sunday) and Holidays	"Mappiness" Study		UK Time Use Survey (Years 2014 and 2015)			
	Mean	Standard Deviation	Mean	Standard Deviation	Normalised Differences	> 0.25?
Activities						
Waiting, Queueing	0.02	0.14	N/A	N/A	N/A	N/A
Working, Studying	0.07	0.26	0.09	0.20	-0.05	No
In Meeting, Seminar, Class	<0.00	0.06	<0.00	0.03	0.03	No
Commuting, Travelling	0.07	0.26	0.08	0.10	-0.02	No
Cooking, Preparing Food	0.05	0.23	0.06	0.07	-0.04	No
Housework, Chores, DIY	0.07	0.26	0.07	0.09	0.02	No
Shopping, Running Errands	0.04	0.20	0.05	0.08	-0.04	No
Admin, Finances, Organising	0.03	0.16	<0.00	0.01	0.16	No
Childcare, Playing With Children	0.06	0.24	0.04	0.10	0.10	No
Petcare, Playing With Pets	0.02	0.16	0.02	0.04	0.06	No
Care or Help for Adults	0.01	0.07	<0.00	0.02	0.05	No
Sleeping, Resting, Relaxing	0.15	0.36	0.11	0.13	0.12	No
Sick in Bed	0.02	0.12	<0.00	0.03	0.11	No
Meditating, Religious Activities	<0.00	0.07	0.01	0.03	-0.03	No
Washing, Dressing, Grooming	0.05	0.21	0.05	0.05	-0.04	No
Talking, Chatting, Socialising	0.20	0.40	0.16	0.19	0.08	No
Intimacy, Making Love	0.01	0.10	N/A	N/A	N/A	N/A
Eating, Snacking	0.12	0.32	0.13	0.09	-0.04	No
Drinking Tea or Coffee	0.08	0.27	N/A	N/A	N/A	N/A
Drinking Alcohol	0.07	0.26	N/A	N/A	N/A	N/A
Smoking	0.01	0.12	N/A	N/A	N/A	N/A
Texting, E-Mail, Social Media	0.05	0.22	N/A	N/A	N/A	N/A
Browsing the Internet	0.05	0.23	0.04	0.08	0.06	No
Watching TV, Film	0.24	0.43	0.20	0.17	0.09	No
Listening to Music	0.07	0.25	0.04	0.09	0.09	No
Listening to Speech or Podcast	0.02	0.14	N/A	N/A	N/A	N/A
Reading	0.04	0.20	0.03	0.07	0.05	No
Theatre, Dance, Concert	<0.00	0.07	<0.00	0.03	0.02	No
Exhibition, Museum, Library	<0.00	0.06	<0.00	0.01	0.05	No
Match, Sporting Event	0.01	0.11	<0.00	0.03	0.08	No
Walking, Hiking	0.02	0.14	0.01	0.04	0.06	No
Sports, Running, Exercise	0.01	0.12	0.02	0.05	-0.02	No
Gardening, Allotment	0.01	0.08	0.01	0.05	-0.06	No
Birdwatching, Nature Watching	<0.00	0.05	0.01	0.04	-0.07	No
Computer Games, Smart Phone Games	0.03	0.18	0.01	0.05	0.13	No
Hunting, Fishing	<0.00	0.02	<0.00	0.02	-0.02	No
Other Games, Puzzles	0.01	0.08	0.01	0.04	-0.03	No
Gambling, Betting	<0.00	0.03	<0.00	0.01	-0.01	No
Hobbies, Arts, Crafts	0.01	0.12	0.01	0.04	0.05	No
Singing, Performing	<0.00	0.07	N/A	N/A	N/A	N/A
Something Else	0.01	0.12	N/A	N/A	N/A	N/A
Other	0.03	0.18	N/A	N/A	N/A	N/A
Company						
Spouse, Partner, Girlfriend, or Boyfriend	0.40	0.49	0.35	0.35	0.08	No
Children	0.16	0.37	0.10	0.25	0.13	No
Other Family Members	0.12	0.33	0.14	0.24	-0.05	No
Colleagues, Classmates	0.02	0.15	0.09	0.19	-0.28	No
Clients, Customers	0.01	0.08	N/A	N/A	N/A	N/A
Friends	0.12	0.32	N/A	N/A	N/A	N/A
Other People You Know	0.02	0.14	N/A	N/A	N/A	N/A
Alone	0.37	0.48	0.29	0.28	0.15	No
Place						
At Work	0.04	0.19	0.06	0.17	-0.09	No
At Home	0.65	0.48	0.62	0.29	0.04	No
Elsewhere	0.31	0.46	0.31	0.27	<0.00	No
Location						
Indoors	0.84	0.37	0.80	0.21	0.08	No
Outdoors	0.10	0.30	0.04	0.07	0.19	No
In Vehicle	0.06	0.25	0.07	0.09	-0.01	No
N	668,573	-	8,245	-	-	-

#	Author	Scope	Methodology	Data	VOT Estimate	VOT (adj.)
1	DeVany (1974)	Air travel demand	Revealed demand elasticities (based on fares, trip distance and flight duration)	Observing largest 600 US air travel markets in 1968	7.28 USD/h (1968)	39.51
2	Crafton (1979)	Supermarket purchasing behaviour: Are time savings worth accepting higher prices? Full price = VOT*time + product price	Revealed consumer demand (choice of store, time-to-purchase & price)	Observing supermarkets (express lanes) & conenvience stores customers	12.58 USD/h (1978)	36.44
3	Cauley (1987)	Demand for medical care	Econometric model to impute the VOT from demand elasticity	Medical records from random sample (California long term medical care patients) + household interviews	7.65 USD/h (1975)	26.85
4	Borisova & Goodman (2003)	Reduction in travel time to repeated mandatory hospital treatment	Stated (contingent valuation): Willingness-to-pay for travel time reduction (WTP); Willingness-to-accept monetary compensation to forego it (WTA)	Patient surveys in Detroit, US in 1999	WTP: 7.32 WTA: 8.65 (wage rate: 9.10) (all USD/h, 1999)	WTP: 8.30 WTA: 9.81 Wage rate: 10.32
5	Portrait et al. (2018)	Children receiving medical care: Three separate units: travel, waiting and treatment time (parent & patient child)	Stated (contingent valuation)	2013-15 surveys in a large Dutch hospital	Waiting: 11.6 Travel: 4.5 Treatment: 3.0 (all EUR/h, 2014)	Waiting: 10.45 Travel: 4.05 Treatment: 2.70

#	Author	Scope	Methodology	Data	VOT Estimate	VOT (adj.)
6	Van den Berg et al. (2017)	Medical patients (non-working, i.e. no wage rate reference; unemployed, retired, long-term sick etc.) Four separate units: Travel, waiting, admission, treatment time	Stated willingness-to-pay for time reduction (contingent valuation)	2011-13 surveys in Netherlands (N=238)	Travel: 2.21 Waiting: 4.05 Treatment: 3.30 (all EUR/h, 2012)	Travel: 2.08 Waiting: 3.82 Treatment: 3.10
7	Wondemu (2016)	Waiting time in public offices	Stated willingness-to-pay for waiting time reduction (contingent valuation)	2011 surveys in Ethiopia, Nigeria and South Africa (N=1,193)	2.38 GBP/h (wage rate: 3.40) (2011)	2.76 Wage rate: 3.94
8	Rotaris et al. (2012)	Travel time among university student commuters	Revealed preferences + stated preferences	n/a	Revealed only: 13-18 Both: 1.4-2.8 (all EUR/h, 2012)	Revealed only: 12-17 Both: 1.3-2.6
9	McFadden (1974)	Waiting times in urban transport Units (bus): walking to station, first wait time, travel time, transit time Comparison to car (total / travel time only)	Valuation at wage rates	Household surveys in California and traffic data (N=213)	Bus waiting: 2.32 Travel: 1.23 Schedule delay: +3.33 Car traffic congestion: +2.13 (all USD/h, 1974)	Bus waiting: 8.89 Travel: 4.72 Schedule delay: +12.76 Car traffic congestion: +8.16
10	Calfee & Winston (1998)	Urban commuting choices (tolled highway car travel vs. bus); Focus on traffic congestion effects on VOT	Revealed willingness-to-pay + stated WTP	Mail surveys across US metropolitan areas (N=1,170)	3.88 USD/h (1993)	5.07

#	Author	Scope	Methodology	Data	VOT Estimate	VOT (adj.)
11	Deacon & Sonstelie (1985)	Motorists' choice of gas stations with longer waiting time but lower gas prices	VOT estimation by occupation, wage income groups	Observations at several California gas stations in 1980 (N=170)	4.46-14.26 USD/h (1980)	10.22-32.69
12	De Vany et al. (1983)	Waiting time in dentist's office	n/a	Survey across dentist practices in US in 1979	8.86 USD/h (1977)	27.62
13	Larson & Shaikh (2007)	Recreational activities (whale watching in California); Framework for VOT estimation that is independent from wage income	Revealed preferences (time & monetary spending for activity)	Surveys at four whale watching sites in US (1991-92, N=1,003)	11.27 USD/h (1992)	15.17
14	Mulligan (1997)	Time as a substitute for money in firms' cash holdings (elasticity of money demand with respect to a proxy for the cost of labor is about 0.6); Higher value of time of a cash manager in a firm is increasing cash holdings; Interesting alternative angle to VOT, otherwise not relevant (in particular, no empirical estimation)				
15	Gronau (1973)	Value of housewife work (opportunity cost of leisure/market work); Interesting alternative angle to VOT, otherwise not relevant				

Supplementary Materials

1. Description of App in Apple's App Store
2. Informed Consent Form
3. Surveys

Description of App in Apple's App Store

Mappiness maps happiness across space in the UK. It's part of a research project at the London School of Economics. We'd love to have you on board!

HOW DOES IT WORK?

- You download the app, open it, and sign up
- We beep you once a day to ask how you're feeling, and a few basic things to control for: who you're with, where you are, what you're doing (if you're outdoors, you can also take a photo)
- The data gets sent back – anonymously and securely – to our data store, along with your approximate location from the iPhone's GPS, and a noise-level measure

WHAT'S IN IT FOR YOU?

- Interesting information about your own happiness, which is charted inside the app – including when, where and with whom you're happiest
- The warm glow of helping increase the sum of human knowledge

WHAT'S IN IT FOR US?

- We're particularly interested in how people's happiness is affected by their local environment – air pollution, noise, green spaces, and so on – which the data from Mappiness will be absolutely great for helping investigate
- We hope to have some results published in academic journals, and elsewhere – whatever we produce will be linked from our website: http://mappiness.org.uk

FIND OUT MORE

For more information, visit http://mappiness.org.uk, or download the app, open it, and choose 'Find out more'.

Informed Consent Form

Please read this information carefully.

By tapping “I agree” below, you confirm that:
- The nature and purpose of this research have been explained to your satisfaction.
- You agree to take part in the study.
- You understand that you can withdraw at any time.
- You’re at least 18 years old, and this is your iPhone.

Please scroll down to see the rest of the information. You can refer back to it at any time in the ‘Info & help’ section of the app.

What’s this research for? We want to better understand how people’s feelings are affected by features of their current environment – things like air pollution, noise, and green spaces.

What will I do? You’ll provide some basic demographic and health-related information, and confirm some settings in order to sign up. After that, you’ll receive a notification (beep) on this iPhone between one and five times a day, at your choice. This will come at a random moment during hours you agree. The notification will prompt you to open this app, to briefly report how you’re feeling and – in very broad terms – who you’re with, where you are, and what you’re doing. If you’re outdoors and you’re happy to, you’ll take a photo of your surroundings too. (You can also open this app and report on your feelings and situation, unprompted, as often as you like).

How long will it take? The sign-up process should take no more than 5 minutes. The daily reports on your feelings and situation will take about 30 seconds each. You can keep taking part in the study for as long (or short) a period as you want.

What data will I be sharing? While you report your feelings and situation, the app will use your iPhone’s GPS (sat-nav) to discover your approximate location. It will also use the microphone to measure ambient noise levels (but it *won’t* record any sound). When you finish responding, the app will send the answers, noise level measure, location data and photo (if you took one) to our secure data store.

What will you do with this data? We’ll use it solely for our academic research. We’ll apply statistical methods to the combined responses from everyone taking part. We’ll use the location data to estimate what the environment was like in the places where people responded. And we’ll be looking at the effect of this on people’s feelings, while controlling for some other potential influences. If you’re curious to see what we find, please visit *mappiness.org.uk* from time to time: we’ll be posting results there. We also hope to present our findings in academic journals and at conferences, and to make sure policy-makers are aware of anything important. In all cases, we’ll never report any individual’s responses – only information at the group level.

And the photos? If you take a photo, we may try to classify it, either manually or using a computer program, to add extra information about your immediate surroundings (for example, are there trees visible?). If you explicitly agree – and we’ll check this with you for every photo – we may also feature it on a public map at *mappiness.org.uk*.

Is it anonymous? Yes. We won’t know who you are. We don’t ask for your name or for any other identifying information, and we don’t need your phone number to send notifications to your iPhone. In principle, given enough responses, it might be possible to identify you from your location data, but we promise we won’t try.

Is it confidential? Yes. We won't disclose your data to any third party unless (1) we're required by law to do so, or (2) we do so under a strict contractual agreement with other academic researchers, exclusively for the purpose of academic research at a recognised institution.

Is it secure? Yes. All communication between this app and our data store is over an SSL-encrypted connection, the same kind used for online banking and shopping. The data store is a firewalled and fully updated Linux server, accessible only over a secure connection.

Is it easy to get out of? Yes! Taking part is completely voluntary. You can withdraw at any time and without giving a reason: just delete this app from your iPhone. You could also ask us to delete all your data from our data store. Alternatively, you can take a break from the study by changing your notifications per day to zero on the Settings screen within the app.

How much data does it use? Not much. Responding to a notification generally uses as much data as sending a brief email (around 1KB). If you're outdoors and take a picture, it's more like viewing a simple web page (15 – 20KB). Getting your status when you open the app uses less than 1KB. Viewing your graphed responses uses about 3KB. So, if you respond to two beeps per day, and you take a photo on 20% of these occasions, you'll use about 350KB per month. (If you have an inclusive data bundle, this is probably less than 0.1% of it.) You may want to turn off data when you're abroad (roaming), though, as this can be very expensive.

I'm not in the UK. Can I take part? You're welcome to, but we may not use your data in our research. And look out for the time difference when setting the hours when you can be beeped: all times in the app are UK times (GMT or GMT+1).

I have another question… If there's anything else you'd like to know, please contact Dr George MacKerron or Dr Susana Mourato:

- Email George at george@mappiness.org.uk. You can do this right now: just tap the button at the top right of this screen.
- Call us on +44 (0)20 3322 4466.
- Or write to us at the Dept. of Geography & Environment, London School of Economics, Houghton Street, London WC2A 2AE.

Thank you!

B.1 Surveys

The surveys span multiple screens, delineated below by horizontal rules. Tapping an option suffixed by '>' immediately advances to the next screen. The first screen has a 'Cancel' button that discontinues the questionnaire, and each subsequent screen has a 'Back' button to return to the preceding screen.

B.1.1 Registration survey

Satisfaction

How satisfied are you with your life as a whole nowadays?

Segmented control: (Not at all) 1 / 2 / 3 / 4 / 5 / 6 / 7/ 8 / 9 / 10 (Extremely)

Next >

Health

Is your health in general... ?

Excellent >

Very good >

Good >

Fair >

Poor >

Asthma

Do you suffer from asthma or other respiratory disease?

Yes >

No >

Gender

Are you... ?

Male >

Female >

Birth year

When were you born?

Scrolling picker: 1900 – 2010 (initial position: 1975)

Next >

Marriage

Are you... ?

Never married >

Married and living with spouse >

Married but separated >

Divorced >

Widowed >

Please choose the first that applies, and treat Civil Partnership like marriage

---

THIS SCREEN IS NOT SHOWN IF THE PARTICIPANT ANSWERED 'MARRIED AND LIVING WITH SPOUSE' ABOVE

Relationship

And are you currently in a relationship?

Yes >

No >

Work status

Are you... ?

Employed or self-employed >

In full-time education >

Retired >

Unemployed and seeking work >

Long-term sick or disabled >

Looking after family or home >

Other >

Adults

In your household, including yourself, are there… ?

1 adult >

2 adults >

3 adults >

4 adults or more >

Please count as adults those aged 16 or above

Children

In your household, are there… ?

No children >

1 child >

2 children >

3 children >

4 children or more >

Please count as children those aged 15 or under

Household

Is your gross annual household income from all sources… ?

Under £8,000 >

£8,000 – £11,999 >

£12,000 – £15,999 >

£16,000 – £19,999 >

£20,000 – £23,999 >

£24,000 – £31,999 >

£32,000 – £39,999 >

£40,000 – £55,999 >

£56,000 – £71,999 >

£72,000 – £95,999 >

£96,000 or more >

Don't know >

Prefer not to say >

We'd be very grateful if you could answer this question, since it's important to our research

---

Income change

Compared to 3 years ago, is your gross annual household income now… ?

Higher than it was >

Just the same >

Lower than it was >

Don't know >

Prefer not to say >

THIS SCREEN IS SHOWN ONLY IF THE PARTICIPANT ANSWERED 'HIGHER THAN IT WAS' ABOVE

Income rise

And finally, compared to 3 years ago, is your gross annual household income now… ?

Higher by up to £999 >

Higher by £1,000 – £1,999 >

Higher by £2,000 – £3,999 >

Higher by £4,000 – £7,999 >

Higher by £8,000 – £15,999 >

Higher by £16,000 or more >

Don't know >

Prefer not to say >

THIS SCREEN IS SHOWN ONLY IF THE PARTICIPANT ANSWERED 'LOWER THAN IT WAS' ABOVE

Income fall

And finally, compared to 3 years ago, is your gross annual household income now... ?

Lower by up to £999 >

Lower by £1,000 – £1,999 >

Lower by £2,000 – £3,999 >

Lower by £4,000 – £7,999 >

Lower by £8,000 – £15,999 >

Lower by £16,000 or more >

Don't know >

Prefer not to say >

THE QUESTIONNAIRE DISMISSES ITSELF IMMEDIATELY AFTER THIS SCREEN IS DISPLAYED

Finished

Thank you!

B.1.2 ESM survey

Feelings

Do you feel... ?

Happy
Slider: Not at all ... Extremely (initial position: midpoint)

Relaxed
Slider: Not at all ... Extremely (initial position: midpoint)

Awake
Slider: Not at all ... Extremely (initial position: midpoint)

Next >

People

Please tick all that apply

Are you... ?

Alone, or with strangers only >

Or are you with your... ?

[ ] Spouse, partner, girl/boyfriend

[ ] Children

[ ] Other family members

[ ] Colleagues, classmates

[ ] Clients, customers

[ ] Friends

[ ] Other people you know

Next >

Place

Are you... ?

Indoors >

Outdoors >

In a vehicle >

Place (2)

And are you... ?

At home >

At work >

Elsewhere >

If you're working from home, please choose 'At home'

TAPPING 'ADD OR EDIT NOTES' DISPLAYS A TEXT ENTRY AREA WITH KEYBOARD — THE PARTICIPANT TAPS 'DONE' WHEN FINISHED TO RETURN TO THIS SCREEN

Activities

Please tick all that apply

Just now, what were you doing?

[ ] Working, studying

[ ] In a meeting, seminar, class

[ ] Travelling, commuting

[ ] Cooking, preparing food

[ ] Housework, chores, DIY

[ ] Admin, finances, organising

[ ] Shopping, errands

[ ] Waiting, queueing

[ ] Childcare, playing with children

[ ] Pet care, playing with pets

[ ] Care or help for adults

[ ] Sleeping, resting, relaxing

[ ] Sick in bed

[ ] Meditating, religious activities

[ ] Washing, dressing, grooming

[ ] Intimacy, making love

[ ] Talking, chatting, socialising

[ ] Eating, snacking

[ ] Drinking tea/coffee

[ ] Drinking alcohol

[ ] Smoking

[ ] Texting, email, social media

[ ] Browsing the Internet

[ ] Watching TV, film

[ ] Listening to music

[ ] Listening to speech/podcast

[ ] Reading

[ ] Theatre, dance, concert

[ ] Exhibition, museum, library

[ ] Match, sporting event

[ ] Walking, hiking

[ ] Sports, running, exercise

[ ] Gardening, allotment

[ ] Birdwatching, nature watching

[ ] Hunting, fishing

[ ] Computer games, iPhone games

[ ] Other games, puzzles

[ ] Gambling, betting

[ ] Hobbies, arts, crafts

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