Happy at work in Africa? Measuring hedonic well-being among water carriers in rural Kenya using the Experience Sampling Method

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Abstract

Despite work's importance in people's overall sense of purpose in life, several studies measuring momentary well-being find that people are very unhappy while at work. These studies have focused on workers in industrialized countries doing paid labor in the formal sector. For a large fraction of humanity, however, "work" is smallholder farming, tending cattle and collecting water and fuelwood. We measure momentary well-being with the Experience Sampling Method in a sample of 195 subjects in rural Kenya. Subjects were the household's main water carrier; 93% were women. Each subject was asked to complete four ESM surveys per day over eight weeks. Results from 9,559 ESM records show that subjects are indeed less happy "at work", whether that work is paid or unpaid casual labor, paid formal sector employment, or resource collection. They are also less energetic, less sociable and in more pain. We also find evidence that subjects perceive themselves as less safe while working or traveling away from home. We find a statistically significant, though small, relationship between the intercepts in the model (individual-level average momentary well-being) and the log of household wages earned over the past two weeks. The relationship is stronger with wages earned by the subject herself.

Introduction

How happy are people while at work? The neo-classical economic view of the time allocation problem (Becker 1965) models people as trading off labor and leisure, where leisure is enjoyable but labor provides disutility – workers either need to be compensated with wages to buy market goods or the product of that labor must be a necessary non-market or subsistence good. The subjective well-being literature, however, points to a seemingly contradictory but extremely robust conclusion: the unemployed report lower overall well-being than the employed, even after controlling for income (Clark and Oswald 1994, Winkelmann and Winkelmann 1998, Theodossios 1998; see Diener et al.1999, Kahneman and Krueger 2006, and

Branchflower and Oswald 2011 for reviews). Part of the answer to the puzzle is that different disciplines have focused on distinct types of subjective well-being: *evaluative* well-being, where people are asked about 'satisfaction with their life as a whole', *eudemonic* well-being, which captures overall feelings of meaning and purpose in life, and *hedonic* well-being in which people rate their momentary feelings of happiness (Larson and Csikszentmihalyi 1983, Dolan and Metcalfe 2012). Kahneman and Krueger (2006) and Kahneman and Deaton (2010) refer to the first two measures as "life evaluation" and the hedonic measure as "emotional well-being" or "experienced utility".

As Bryson and MacKerron (2017) point out, the measurement of moment-by-moment happiness harkens back to economist's original conception of utility – both measurable and cardinal and thus amenable to inter-personal comparison, as in Francis Edgeworth's hedonimeter. Measuring it, however, is far harder than evaluative measures that can be asked with a handful of questions and compared using large cross-country surveys. One hedonic approach - the Experience Sampling Method (ESM) - asks respondents to answer a short survey that asks about the person's activity and feelings at a randomly-selected time of day over many days or weeks, and typically during many points throughout the day (Larson and Csikszentmihalyi 1983, Csikszentmihalyi 2014). This allows both a statistical reconstruction of time use that is not prone to recall bias as well as hedonic measures of well-being during activities. It does, however, place a heavy demand on respondents, and the technology used during its conception in the 1970's (pagers, paper forms) limited the number of respondents that could be recruited. The advent of networked, low-cost smartphones has dramatically lowered the cost of administering large numbers of ESM surveys, though the respondent burden remains high. The Day Reconstruction Method (DRM) of Kahneman et al. (2004) is similar but less resource-intensive since it asks respondents to "relive" the prior day and their affective states throughout. As we will discuss below, results from several DRM or ESM studies in industrialized countries find that people generally experience lower momentary well-being while at work (Kahneman et al. 2004, Knabe et al. 2010, Killingsworth and Gilbert 2010, Bryson and MacKerron 2017).

The primary contribution of this paper is to test whether these results also apply to a quite different setting: rural Kenya. “Work” in these settings is less likely to be salaried formal-sector labor (World Bank 2021). Much more common is manual labor on smallholder farm plots, either on one’s own plot or working for barter or cash on another’s, resource collection, or tending to livestock. A second contribution is that we provide a rare picture of the “experienced utility” of people’s lives and activities – inside and outside of “work” – in a rural region of a low-income country. We know of only one other application of the ESM or DRM method in such a setting. Miñarro et al. (2021) measured momentary well-being in Bangladesh and the Solomon Islands, but used the ESM data only to explore mean momentary affect; they did not describe or explore the relationship between momentary well-being and activities. We believe studies like Miñarro et al. (2021) and ours are critical additions to this literature because of the well-known bias in psychological and behavioral studies towards subject pools that are WEIRD (Western, educated, industrialized, rich and democratic) (Henrich et al. 2010, Hendriks et al. 2019).

We report the results of the ESM approach on a sample of 195 subjects in rural Meru County, Kenya. As described further below, we focused our study on the person in the household who was primarily responsible for water collection, typically a woman. Few men in rural Kenya (and in our site) collect water, so our results should be interpreted mainly with respect to women. Furthermore, it is possible that the household’s “main” water carrier may be systematically different from other adult women in the household, either through preferences for collecting water or physical ability. Strictly speaking, the external validity of our results extends only to adult water carriers. We believe it is likely, however, that our results could berepresentative of working age women in rural Kenya or perhaps even east Africa. We asked respondents to complete a short, custom-designed survey on a low-cost smartphone four times per day, six days per week, over eight weeks in August – October 2016. The survey asked them to report primary and secondary/concurrent activities, who they were with, and a series of affect questions. We report results from a total of 9,559 ESM records after data cleaning, though we also find similar results using a less-conservative data cleaning algorithm.

We find that, compared to household work (our base activity for comparison), subjects are less happy when the ESM survey found them farming, collecting water or firewood, or doing informal or formal sector work. Two results are tenuous but intriguing for the wider question of happiness and work: the self-employed are happier while at work, and people are less happy when they reported their primary activity as "having nothing to do". We also find a statistically significant, though small, relationship between the intercepts in the model (individual-level average momentary well-being) and the log of household income.

Literature

A vast literature has explored subjective well-being as measured in evaluative "overall life satisfaction" measures. These include many international comparisons including subjects from low- and middle-income countries (see Howell and Howell 2008, Blanchflower and Oswald 2011, and Blanchflower 2021 for surveys and recent results). A dominant focus has been exploring the correlation between income and overall life satisfaction, following Easterlin's (1974) observation that economic growth has not led to increased levels of subjective well-being. A common finding is that absolute income, rather than relative income, matters for life satisfaction of the poor more than the rich because extra income helps meet basic needs. As households meet basic needs, income comparisons become more important (Jebb et al 2018). Reyes-García et al. (2016) confirms this finding in 6,973 rural households in 23 countries throughout Asia, Africa, and Latin America. They also confirm findings from studies in industrialized countries on life satisfaction correlates such as marriage, trust, illness, and income inequality, though not age.

Our focus in this article is on hedonic or momentary well-being. As described above, the measurement of people's "experienced utility" is much more challenging and burdensome to subjects than evaluative life satisfaction measures that can be asked with one or a small number of questions in large, nationally representative surveys. Assessing momentary well-being using the ESM (Larson and Csikszentmihalyi 1983) or related Ecological Momentary Assessment (EMA) (Shiffman et al. 2008) requires subjects to assess emotions during activities as they happen. As Knabe et al. (2010) note, the advantage of the ESM 'is that it allows the

measurement of experienced utility without any distortions caused by aspirations, retrospective evaluations or memory effects. Results from ESM studies in industrialized countries have given rise to the concept of highly satisfying "flow" states (Csikszentmihalyi 2014) and shown that momentary unhappiness is more strongly associated with wandering minds than with specific activities (Killingsworth and Gilbert 2010). Kahneman et al. (2004) developed the Day Reconstruction Method (DRM) to combine time use diary information with subjects' self-assessed emotional states during recalled "episodes" from the previous day.

Despite their value in "accounting for the richness of daily activities" (White and Dolan 2009), studies assessing hedonic well-being using either the DRM or ESM approach in a low-income country are almost non-existent. DeVries et al. (2020) reviewed 53 smartphone-based ESM or EMA studies; all were in industrialized countries. One recent study (Miñarro et al. 2021) measured momentary well-being in Bangladesh and the Solomon Islands among 77 fishers in four communities. The ESM questionnaire was not self-completed, as is standard, but assessed with a brief phone call to the subject's phone at two random times per day for one week. Miñarro et al. (2021) combine average overall momentary well-being from this exercise with an evaluative well-being measure and net affect from the previous day to explore the role of monetization in subjective well-being. The researchers did not describe the relationship between momentary well-being and activities.

Like Bryson and MacKerron (2017), we use our ESM data to ask primarily whether people enjoy "work". One hypothesis is that human beings take pleasure from work because it is intrinsically satisfying (Hinchliffe 2004). The alternate hypothesis, usually associated with economists, was outlined at the start: people dislike work. They will work, reducing their leisure time, only to earn money to buy goods and services or to undertake subsistence activities. The available evidence, all from industrialized countries, supports the latter. In a sample of 909 women in the US who had done paid work, Kahneman et al. (2004) find that time spent at work was rated second to lowest in overall happiness. In another DRM study, White and Dolan (2009) find that work is the activity with the lowest overall mean "pleasure" response among 625 German subjects, though it was rated highly on a "rewarding" dimension. Using a very large but self-selected sample willing to participate in an ESM smartphone app,

Killingsworth and Gilbert (2010) also find "work" to be the second worst activity in mean happiness. Using data on over one million ESM records from 20,000 individuals in the UK who self-selected by downloading the "Mappiness" app, Bryson and MacKerron (2017) also find people are unhappy at work: paid work is ranked as the least enjoyable of 39 activities, with the exception of being sick in bed. Both Bryson and MacKerron (2017) and Kahneman et al. (2004) found that working from home made respondents somewhat less unhappy, as did working with others. Knabe et al. (2010) use a DRM approach in a German sample to explore the effects of unemployment on momentary well-being, confirming that the employed are unhappy at work[1]. How to increase happiness at work has long been of interest among management researchers who have explored group and organizational determinants of well-being on the job (see Fisher 2010 for a comprehensive review).

Do these findings hold for "work" in rural Kenya? Although our sample includes a small number of salaried workers (who likely work in offices), women's labor in rural areas of low-income countries is unpaid and a large fraction of their overall time use. Collecting water and firewood and working on non-mechanized farm plots is physically demanding drudgery, so one might expect rural Kenyans would be even unhappier at work. On the other hand, such work is outdoors which may increase momentary well-being (White and Dolan 2009), and women may enjoy the physical exercise, the autonomy from their husbands while working away from home, or the time away to socialize[2]. Like Bryson and MacKerron (2017), we explore the association between work and momentary well-being and how it varies by time of day, whether one is alone at the time, and individual characteristics. Unlike DRM studies that only capture a single

[1] Knabe et al (2010) suggest that unemployment affects well-being through two channels. Unemployed people feel worse than employed people when engaged in similar activities (the "saddening effect"), but the unemployed have the ability to re-allocate their time to activities that bring more pleasure (the "time composition effect"). They also find that the employed are unhappy at work and confirm that the unemployed show lower episode satisfaction (White and Dolan 2009) during all activities and report lower general life satisfaction. But they find that the time composition effect balances the saddening effect overall, so that day-to-day satisfaction is the same in both groups.

[2] The belief that women enjoy water collection is so ubiquitous in the water sector that it has even made it to Hollywood. In the movie "Whiskey Tango Foxtrot", Tina Fey plays a journalist in Afghanistan who embeds with an army unit that keeps returning to the same village over and over again to repair its water source. Each time the military (and the men in the village) believe the Taliban has destroyed the water point. Finally, a local woman furtively takes Fey's character aside to reveal a cabal of village women who have been plotting to destroy the well because collecting water from farther away allowed time away from their husbands.

day for each respondent, our longitudinal data also enables us to focus our attention on variation in experienced utility within individuals over time, using individual fixed effects to capture unobserved differences across individuals.

Study site and respondents

We conducted baseline interviews with a total of 248 households in four "sublocations" in the Tigania West political constituency, Kenya. The sublocations are rural areas with no paved roads and clustered around the small market town of Kianjai. Kianjai is connected by 19 kilometers of paved road to the larger city of Meru, in the shadow of Mt Kenya in eastern-central Kenya. Meru County is a relatively fertile and important agricultural area, though our study site receives less rainfall than the agricultural areas around the city of Meru. Predominant crops in our Tigania West constituency are grams, peas, cassava and mangoes, and many households raise commercial livestock (Kenyan Bureau of Statistics 2015).

The study site was chosen purposefully in 2013 for a study of households' water source and collection decisions. Sample households in 2016 were chosen randomly based on a transect approach, but because of the overall research agenda we excluded households who had a well or piped water on premises or did not have at least one school-aged child at home. We provide more details on the sampling approach in Appendix B.

A team of ten trained enumerators asked households a number of detailed questions in Kimeru, the local language. We interviewed the household member "who is mostly responsible for water-related decisions such as where to get water and how much to collect'', but asked that the phone and ESM survey (described below) be deployed with the person in the household who spends the most time collecting water, whom we refer to as the main water carrier. Our focus in this paper is on water collectors because it is part of a larger research project that tested the impact of reducing water collection times on time use, affect and school outcomes. Selecting the main water carrier does not, however, mean the momentary well-being data from our subjects is unrepresentative of women in these settings. Fetching water is one of the largest components of unpaid work in developing countries, and it is done largely by adult women (Sorenson et al. 2011, Graham et al. 2016).

Of these 248 households, 12 dropped out of the study and did not provide any meaningful number of ESM surveys. We dropped an additional eight households because enumerators expressed multiple concerns that the person carrying the phone was not the main water carrier. Further data cleaning, described below, dropped all of the ESM records for some households, leaving a total sample of 195 households.

Who were the water collectors who carried the phones and completed the ESM surveys? The typical (median) person was a 37-year-old woman with eight years of education who could read "with difficulty". Overall, only 7% (n=13) were men, who were slightly older (median of 40 years old). We include two subjects who were 12 and 16, though we will refer to subjects throughout as adults[3]. The oldest subject was 72. Sixty-seven percent of phone carriers were age 40 or under (the full distribution is shown in Appendix Figure A 1). Approximately half could read "with difficulty", 25% could read "easily" and 23% could not read at all. In 90% of households, the person carrying the phone identified herself as both the "main water decision maker" and the person who spends the most time collecting water. Nearly all (98%) said that they work on the household's own farm, and 35% said they have worked for wages in the past two weeks. On average, they had worked for 4.7 days in the past 14 and earned an average daily wage of 254 Kenyan shillings (Ksh), about USD 2.49 (~102 Ksh/USD in August 2016). Among those who worked for wages, 29% said the wage work was casual labor, 40% performed wage labor on someone else's farm, and 23% were self-employed entrepreneurs. Only four respondents were employed in the formal sector.

ESM Methods

Each participating household was given a low-cost (USD 20) smartphone as well as a solar charger kit to make sure the phone would remain charged. Each also received a SIM card; each SIM card account was loaded daily with enough airtime credit to transmit any completed forms. Network coverage, however, sometimes prevented the user from submitting the form

[3] Although only two of our "main water carriers" were children, other children were collecting water in these households. A typical household had one or more children collecting water, but this was to supplement water collected by the main water carrier, typically the mother, who is our focus here. These estimates are roughly in line with rural Kenya overall. The 2014 Kenyan DHS found that the person "who usually collects water" is a woman over age 15 in 77% of rural households, a man over 15 in 19% of households, and a child younger than 15 in 5% of households.

exactly as it was completed, but the forms were stored (and time-stamped) in the phone to be sent in batch when the phone connected with the network.

Our survey was conducted on a custom Open Data Kit (ODK) app designed by the research team. The survey asked about what the respondent was doing when the phone buzzed, with 18 time use categories. The order in which the categories were shown to the respondents was randomized in ODK each time a respondent completed an ESM survey. Each category was represented by a picture, and accompanying text gave a description of the activities that respondents should include in that category. Descriptions (see Appendix Table A 3) were revised with input from focus groups and the enumerators, and back translated into Kimeru, the local language. They were also designed to map to the UN Time Use standard categories (UN Statistics Division, 2016). The time use categories and descriptions were carefully explained to each participant during a baseline survey.

We made the ESM program flexible for users to interact in the way most comfortable to them. Since many educated Kenyans prefer to read in English, the category headings could be shown in either English or Kimeru with a menu option on the program. We also assigned a photo for each category to help illiterate users. Users could push a button to have the program play back a recording of each of the detailed descriptions for each activity, read in Kimeru. The ESM survey also asked: a) follow-up labor questions for households who said they were farming, going to market or working that asked the type of work, if they worked for wages, and if they worked for themselves or others, b) how much they enjoyed the activity, c) whether it was important to them and others, d) whether they wished they had been doing something else, e) a secondary (concurrent) activity (if any), f) who they were with when the phone buzzed, g) whether they were in any physical pain or discomfort, h) whether they felt safe, and i) affect on three dimensions (happy vs. sad, tired vs. energetic, lonely vs. sociable)[4]. Each of the affect measures were asked of respondents as a 7-point Likert scale. For the happiness measure, for example, the options were "very sad" (coded in the data as 1), "quite sad" (2), "a bit sad" (3), "neither happy nor sad" (4) and "a bit happy" (5), "quite happy" (6) and "very

[4] The underlying file needed to replicate the ODK survey are available at https://tinyurl.com/y8o33vcm , and a video showing how the app would have looked and sounded to respondents (on the actual phones) is at https://www.youtube.com/watch?v=L1MBUk4ldfk .

happy" (7). We follow Bryson and MacKerron (2017) and others in assuming cardinality of the categories and we transform them onto a 0 to 100 scale for ease of interpretation, where 0 is "very sad", "quite sad" is assigned 16.7 (100/6 intervals), "a bit sad" is 33.3, etc. up to "very happy" (100). The question on safety was asked on a 4-point scale (very unsafe, somewhat unsafe, somewhat safe and very safe) and similarly transformed to a 0 to 100 scale. The options for the question on physical pain were "none", "slight pain" and "severe pain". Since these response options are less likely to be cardinal, we collapse this into a dummy variable that is equal to one if the respondent reported either slight or severe pain. We did not ask questions on summary evaluative life satisfaction.

To generate a randomly timed prompt to complete the survey, we adapted an existing Android app called Randomly Remind Me. The app generated a reminder at four randomly chosen times of the day (during waking hours), six days a week. The reminder included a pop-up message that would open the ODK app automatically when clicked. The program should have logged when each reminder was issued, allowing us to check whether respondents clicked immediately after the reminder rather than after some delay. Unfortunately, this functionality did not work well in the field and we were unable to verify when respondents answered questions with the Randomly Remind Me app. We instead rely below on the timestamps of submissions in ODK, which worked properly, to argue that respondents seem to have replied to reminders promptly but also flag potentially problematic records.

The household member who spends the most time collecting water was supposed to be the person completing the ESM surveys. To guard against the phone being taken by another household member, we used a pictorial password. We asked the main collector in the baseline survey to choose among a list of pictures of East African animals. That would be her "secret animal" that she should not share with others. The first question of the ODK survey asked for this animal as a password, and we did identify cases where the animal was inconsistent, and the team learned that someone else had been using the phone. In each case, a member of the team visited the household to emphasize that the main water carrier was the person who needed to carry the phone, and that their participation in the program could end, costing them the smartphone and solar charger).

Phones were deployed to households beginning on August 19th, 2016. As described in Appendix C, we dropped a total of 4,450 ESM records that a) could not be matched back to a household based on the phone's unique ID; b) were records likely generated during training or programming of the phones; c) had implausible time stamps from the network; or d) had an incorrect "password" and were thus likely filled to have been filled out by another household member. In an additional 9,934 ESM records, the timing and length of ESM records suggests that the survey was either not completed immediately after being prompted or was completed without any prompting at all (e.g. completing more than four surveys per day). Rather than discard these records, we flag them as potentially problematic. The results presented below do not use these records and are estimated on a final sample of 9,559 records from 195 respondents, though sample sizes vary by measure because of item-level missing data[5]. We present a sensitivity analysis in Appendix D of the same models estimated on the "full" dataset (n=19,493 from 220 households) that includes these flagged records, showing the two sets of results side-by-side. Results are almost always very similar; we note differences in the results section below.

Among the 9,959 records in our main data, Panel A of Figure 1 shows that the number of submitted surveys in total varied fairly little over the time period of the study, and Panel B shows a similar pattern of average submissions per person. Note that this average is less than four: as expected, respondents did not on average respond to all four prompts from the phone each day. Panel C shows that surveys were submitted throughout the day, and Panel D shows balance by day of the week. Finally, Panel E shows the time between when the ESM program was started by the respondent and when it was submitted. This excludes flagged records where the completion time exceeded 15 minutes. The average and median times were 3.2 minutes and 2.6 minutes; 85% were under five minutes[6].

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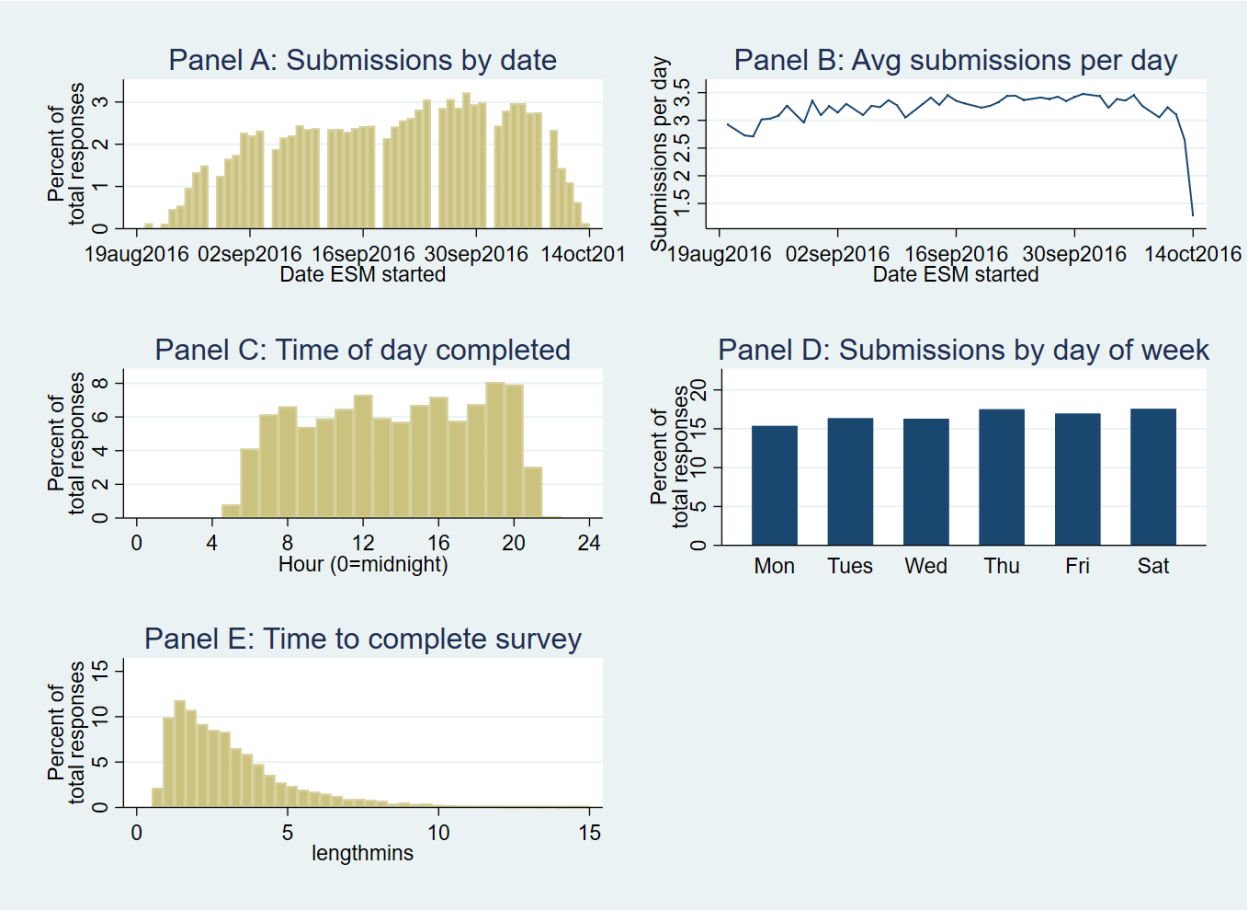
[5] Respondents could skip any question within the ESM survey except the password ("secret animal"). Although we have n=9,559 ESM records with an activity listed, some subjects skipped some of the affect or explanatory questions. In 90 ESM records, for example, subjects reported a main activity but failed to complete the "happy-sad" question, leaving us with n=9,469 records for our key dependent variable. Including controls for "alone" further reduces usable records for the regression.

[6] Appendix D shows the same diagnostic charts for the full set of ESM records. Since we flagged records that took longer than 15 minutes to complete or records from phones where more than four ESMs were completed per day,

Figure 1. ESM survey diagnostics



Notes: n=9,959 records from 195 households.

Empirical strategy

We exploit the panel nature of the dataset to explore how different activities are associated with changes in momentary well-being. The dependent variable is the response to each of the affect questions, scaled from 0 to 100 as described above. By estimating a model with person- fixed-effects, we exploit variation within each person's reporting of their happiness, safety, etc. as it varied by the activity that the ESM found them doing. The key regressors are a set of dummy variables for each activity type. Since these are exhaustive

the most notable differences are in Panels B and E. Panel B shows a large spike in submissions per day early in the research project when respondents were learning how to use the program. Panel E shows a long right tail in time to complete the record, likely driven by people partially completing the ESM survey and finishing it later. Although the median time increases only from 2.6 minutes to 3.2 minutes when including the flagged records, the mean increases from 3.2 minutes to 110 minutes.

categories, we exclude a dummy for "household work". We chose household work because a) it is the most commonly reported activity (see Table 1) and b) it is approximately equal to the overall mean level of happiness across activities. The average happiness during household work is 81.1 on our 0-100 scaled measure. This implies that coefficients should be interpreted as a change in the 0-100 scaled measure (e.g. happiness) relative to the average level reported in the sample when doing household work, or roughly the mean overall happiness level. Although it is not strictly speaking a percentage, we will refer to these coefficients as percentage changes, so that a positive coefficient of 6 points on the 0-100 scale is a 6% increase in happiness. The specific estimation model is:

$$(1) \qquad h_{it} = \propto_i + \beta_{A_j} A_{j_{it}} + \gamma x_{it} + \epsilon_{it}$$

where *h* is the affect measure (0 to 100) of individual *i* at time *t* while doing activity A_j. Standard errors are clustered at the person level to account for non-independent repeat observations[7]. $\propto_i$ is the fixed effect that captures person-specific heterogeneity in overall affect during the study. ϵ_{it} is the error term. We estimate a panel logit on our binary measure of pain (the percent who felt moderate or severe pain).

We also include a set of covariates x_{it} for other characteristics of that moment that may explain momentary well-being: whether the person reported being alone, and time of day (morning (5am-noon), afternoon (noon-5pm) or evening (5pm – 11pm), with morning as the excluded category). Appendix Table A1 reports regression results with and without these controls; our key results are unchanged without these controls. Unlike Bryson and MacKerron (2017), we see no effects of being alone or time of day on average happiness. Respondents are more likely to report feeling tired but more sociable as the day wears on. All models reported hereafter include these controls. We also ran gender-disaggregated models, though they are underpowered given the small number of men in our sample who are the primary water

[7] Implemented with *xtreg,fe vce(cluster)* in Stata 15. We also explored random-effects models to increase efficiency and reduce standard errors. Hausman tests of fixed-effects vs. random-effects models for each of the four measures indicated that random-effects models would be consistent for the sociability and safety measures (fail to reject null of no systematic difference in coefficients at p=0.72 and p=0.58). For happiness and energy, however, the test statistics imply that random effects models are inconsistent (reject null at p=0.0246 for happiness and p=0.034 for energy). To avoid confusion, however, we report fixed-effects results for all four measures throughout. Results from RE models for sociability and safety are indistinguishable and available on request.

collector (n=13). Although the signs of most coefficients are the same for men, most are not statistically significant (results available on request).

The relationships we uncover are correlative; we do not claim causality. In the research design here we cannot know, for example, whether working on the farm makes a subject less happy, or a subject chooses to do farm work when she is already feeling less happy.

Finally, we explore relationships between individual observable characteristics and the $\propto_i$ in equation 1, which represent each respondent's estimated average level of happiness, pain, sociability, etc. compared to the group-level average.

Results

Summary statistics

We begin with a description of the summary statistics for affect and time use (Table 1). Overall, respondents report being fairly content: the average value across all observations is 79 on a scale of 0 (very sad) to 100 (very happy), between "a bit happy" and "quite happy". Respondents generally report lower levels of happiness while they are collecting water or firewood, are doing paid or unpaid casual labor, or describe themselves as being idle. Similarly, on average, respondents reported feeling somewhat sociable (mean=64), but feeling more sociable during meetings and, of course, when their main activity was socializing. Our measures on the tired versus energetic scale demonstrate the overall content validity of the exercise: respondents report feeling least energetic (overall mean = 38) when the ESM has captured them in tiring manual work: collecting water or wood, farming, casual labor, or going to market. Similarly, a higher fraction of respondents reported feeling moderate or severe physical pain in the past hour (overall mean = 22%) when their primary activity is resource collection, farming or casual labor. There is little apparent difference in perceptions of safety (overall mean = 73) by activities. Finally, our measure of agency (percent who said they were doing the activity because they "wanted to") is highest for entertainment (TV or radio), socializing, studying or sports/hobbies. Only 6% said they were doing the activity because they "had nothing else to do"; the majority (79%) said it was because they "had to". However, the small number of men in our sample were more likely to report doing an activity because they wanted to than women (26% of records for men vs. 15% for women, *t-statistic* for difference= 8.39). It is possible that

some activities are under-reported because of privacy concerns. This was the reason we created a catch-call “Private” time use category, rather than asking subject about sexual activity, for example. The possibility of non-random non-response is a limitation our approach shares with any time use elicitation method or momentary well-being study.

Table 1. Summary statistics of time use and affect, by activities

Activity	ESM records		Happy	Sociable	Energetic	Safe	% Some Pain	% Want to	% Wish do Else
	Number	Percent	mean (se)	mean (se)	mean (se)	mean (se)	mean (se)	mean (se)	mean (se)
Caring for others	481	5.03	84.5 (0.87)	64.8 (1.38)	39.9 (1.3)	74.3 (1.12)	16.6 (1.7)	7.3 (1.2)	11.8 (1.5)
Work priv. business	60	0.63	82.5 (2.74)	67.5 (3.94)	42.5 (3.23)	71.8 (3.2)	20.3 (5.3)	21.7 (5.4)	3.3 (2.3)
Tending livestock	393	4.11	82.4 (0.92)	60.5 (1.68)	37.6 (1.34)	72.2 (1.32)	19.9 (2)	9.9 (1.5)	12.1 (1.7)
Going to market	502	5.25	81.9 (0.85)	65.6 (1.41)	34.8 (1.32)	71.6 (1.23)	24 (1.9)	20.7 (1.8)	10.1 (1.4)
Attending meetings	631	6.6	81.4 (0.87)	68.3 (1.23)	44.0 (1.09)	71.4 (1.06)	10.5 (1.2)	13.5 (1.4)	10.6 (1.2)
Bathing, Pers.Care	374	3.91	81.3 (1.01)	59.0 (1.74)	42.5 (1.53)	72.1 (1.31)	16.2 (1.9)	16.6 (1.9)	10.3 (1.6)
Sports, hobbies	26	0.27	81.3 (4.12)	63.5 (6.13)	39.3 (6.08)	64.1 (5.21)	34.6 (9.5)	53.8 (10)	7.7 (5.3)
Household work	2828	29.58	81.1 (0.38)	66.3 (0.59)	39.3 (0.54)	74.4 (0.46)	16.7 (0.7)	8.7 (0.5)	8.9 (0.5)
Studying	135	1.41	80.2 (1.86)	59.7 (2.77)	47.5 (2.54)	73.3 (2.35)	19.8 (3.5)	34.1 (4.1)	11.6 (2.8)
Socializing	820	8.58	79.1 (0.76)	71.2 (1.03)	43.7 (0.98)	73.2 (0.89)	15.4 (1.3)	34.8 (1.7)	17.4 (1.3)
Private	141	1.48	79.0 (1.84)	51.5 (2.74)	45.3 (2.41)	78.1 (2.35)	12.9 (2.8)	29.8 (3.9)	22.9 (3.6)
Radio or TV	283	2.96	79.0 (1.33)	62.9 (1.89)	41.2 (1.79)	75.5 (1.61)	17.4 (2.3)	42.8 (2.9)	18.5 (2.3)
Attending school	60	0.63	78.1 (3.28)	58.9 (4.38)	41.7 (3.66)	68.4 (3.73)	25 (5.6)	23.3 (5.5)	5 (2.8)
Sleeping	378	3.95	77.8 (1.2)	58.6 (1.78)	42.6 (1.47)	71.2 (1.35)	20.2 (2.1)	22.8 (2.2)	14 (1.8)
Collecting firewood	211	2.21	77.3 (1.58)	54.0 (2.42)	24.9 (1.81)	70.3 (1.93)	28.2 (3.1)	14.2 (2.4)	25.2 (3)
Farming, own	781	8.17	75.0 (0.78)	57.8 (1.16)	31.4 (0.97)	70.9 (0.97)	40.5 (1.8)	10.5 (1.1)	15.3 (1.3)
Idle	170	1.78	74.9 (1.73)	59.3 (2.6)	43.3 (2.12)	72.8 (2.12)	18.9 (3)	28.2 (3.5)	38.1 (3.8)
Casual labor, unpaid	108	1.13	74.8 (2.08)	61.7 (2.87)	34.1 (2.75)	73.5 (2.59)	34.3 (4.6)	17.6 (3.7)	27.1 (4.3)
Collecting water	902	9.44	73.2 (0.73)	62.6 (1.08)	29.3 (0.96)	71.1 (0.9)	37.6 (1.6)	7.2 (0.9)	38.4 (1.6)
Farming	13	0.14	72.9 (7)	64.6 (8.59)	30.9 (8.47)	73.4 (6.67)	12.5 (12.5)	0 (0)	45.5 (15.7)
Casual labor, paid	248	2.59	72.8 (1.46)	65.4 (2.03)	28.5 (1.88)	69.5 (1.7)	30.6 (2.9)	22.2 (2.6)	38.5 (3.1)
Paid formal labor	12	0.13	72.2 (6.27)	59.7 (6.94)	40.3 (7.52)	75.0 (7.25)	16.7 (11.2)	33.3 (14.2)	25 (13.1)
Otherwork	2	0.02	66.7 (33.35)	58.4 (8.35)	75.0 (25)	66.7 (0)	0 (0)	100 (0)	0 (0)
OVERALL	n/a	n/a	79.2 (0.22)	63.9 (0.33)	38.1 (0.3)	72.8 (0.27)	21.7 (0.4)	15.7 (0.4)	16 (0.4)
TOTAL n =	9,559		9,469	9,446	9,460	9,483	9,489	9,559	9,456

Notes: Note that 10% of records implies 93 minutes for a 15.5 hour day; one hour (60/930 minutes) = 6.45%. Affect questions were asked: "Please describe how you are feeling right now in terms of being…" happy vs. sad, tired vs. energetic, sociable vs. lonely. Each was asked as a 7-point Likert scale but recoded to 0-100 scale. For the happiness measure, for example, the response options were "very sad", "quite sad", "a bit sad", "neither happy for sad", "a bit happy", "quite happy", and "very happy". Safety ("During the last hour (before the phone buzzed), did you feel unsafe?") was asked on a 4-point scale (very unsafe, somewhat unsafe, somewhat safe and very safe) and similarly transformed to a 0 to 100 scale. Pain ("During the last hour (before the phone buzzed), did you feel any physical pain in your body?") was left as a categorical variable; we report above the percent who answered "slight pain" or "severe pain", rather than "no pain". We asked "Why were you doing this activity?"; "Want to" reports the percentage who said it was because they wanted to, not because they "had to". The final column reports the percentage who said yes to "Do you wish you had been doing something else?" See Table A3 for full descriptions of activities, with Kimeru translations. The underlying file (an Excel spreadsheet) needed to replicate the ODK survey is available at https://tinyurl.com/y8o33vcm (*PERMANENT URL ON PUBLISHING*).

Finally, we asked respondents who they were with when the phone buzzed. They were alone 43% of the time, with a friend in 32% of records, with a relative in 19% of records, and with a neighbor or stranger in 6%. Respondents were, of course, less likely to report being alone when the primary activity was attending meetings, socializing, or going to market.

Panel (individual fixed-effects) regressions

Although the conditions of "work" and study population were different from those in Kahnemann et al. (2004) and Bryson and MacKerron (2017), our results are generally consistent with their central findings: respondents were less happy (compared to household chores) when the ESM exercise found them doing work like collecting water, collecting firewood, farming, or doing casual paid labor (Figure 2 plots regression coefficients; full regression results are reported in Appendix Table A 2). Note that because these models control for whether the respondent was alone or socializing, we can rule out the possibility that the utility of socializing while working outweighs the disutility of working[8]. Water collection and firewood collection are associated with 6.7% and 3.2% decreases in happiness compared to household chores. Casual labor is associated with 6.1% drop in happiness when the work is paid. The point estimate for unpaid casual labor is also negative but not statistically significant in our main analysis sample, though it is in the full set of ESM records including those flagged as potentially problematic.[9] Being "at work" when the job is in the formal sector may be even worse: the point estimate implies these respondents are 9.3% less happy when at work, though this result is not statistically significant because there are so few respondents with formal sector jobs. Unlike Kahneman et al. (2004), we find no statistically-significant decrease in happiness when the respondent is "caring for others", which is predominately childcare in our population.

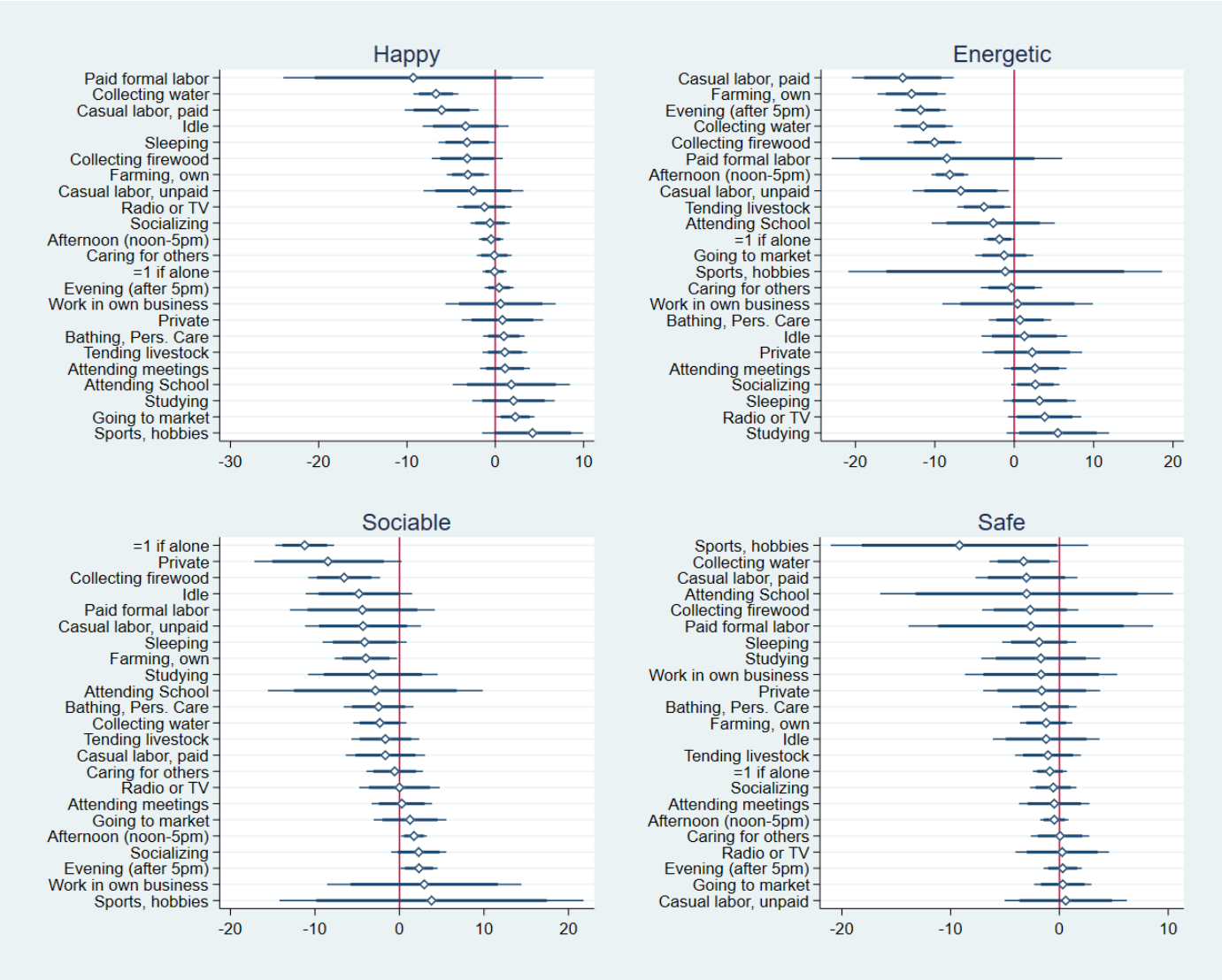
To make our results directly comparable to Bryson and MacKerron (2017), we estimate a model where we define "work" as wood or water collection, livestock husbandry, working on one's own farm, informal work (paid or unpaid), formal paid work or working in a private

[8] Because there is a perception that water collection is a social activity, we also estimated a model with an interaction term on being alone and collecting water to capture anything special about being with others while collecting water. The coefficients on water collection and being alone barely change, and the interaction term is not statistically different from zero.

[9] When including the full set of ESM records, the coefficients on paid and unpaid casual labor are close to each other (-5.41 and -5.71) and both statistically significant at the 1% level. See Appendix C.

business. Unlike the results above where household chores are the omitted time category, this formulation implicitly treats all "non-work" activities as the reference category. Subjects were 4.1 points less happy when "working" (t-stat = 7.0, full results available on request), compared to the 8.2 point drop observed in Bryson and MacKerron (see their Table 2; fixed effects model among workers only).

Figure 2. Coefficients from fixed-effects panel regression model of happiness, energy, sociability, and safety.



Notes: Coefficients plotted from panel regression model (xtreg). Standard errors clustered at the person-level. Thicker line represents 95% confidence interval; thinner line 99%. Regression on happiness based on 9,444 records, energetic (n= 9,433), sociable (n= 9,417), safe (n=9,451). All four regressions use data from 195 subjects. All four measures were recoded (as cardinal) from original 4 or 6 answer codes to a 0-100 (cardinal scale); see text.

Some types of activities that might be considered work seem to be more enjoyable. People are 2.3% happier on days when they travel into town to shop, sell, and socialize ("going to market"). Those with experience in rural African settings will know that going to the market is often a highly-anticipated social activity that is the highlight of many people's week. The coefficient on "tending livestock" is positive but not statistically significant. We also find one weak but intriguing result: those who are self-employed may be *happier* at work. The point estimate on "work in own private business" is positive but not statistically significant in our main regressions. Using the larger set of ESM records that includes some records that were flagged as potentially problematic, however, our results imply that entrepreneurs are 3.7% happier while at work compared to doing household work (significant at the 1% level; see Appendix C). "Leisure" activities like reading, TV/radio, sports, bathing and personal care, or socializing are generally not statistically different from household work, though point estimates are typically positive. We also find that people were also 4% *less* happy when their main activity was being idle ("doing not much of anything").

Physically demanding activities like water collection, firewood collection, farming, and casual labor are also associated with statistically significant drops in energy and sociability compared to household work. Respondents report feeling 12% less energetic and 2% less sociable when they are collecting water. Firewood collection is associated with being 7% less sociable and 10% less energetic. Farming on the household's own farm is associated with being 4% less sociable and 13% less energetic. Manual labor like water or firewood collection, farming or casual labor are also associated with a higher probability that the respondent reported being in "slight" or "severe" pain (Figure 3). Respondents are also more likely to report pain in the afternoon or the evening, compared to the morning.

Our respondents, who were predominately women, generally reported feeling more unsafe when they were doing activities away from the home. Respondents reported feeling 3% less safe when they are collecting water. This provides support for a claim that has often been discussed in the water supply and sanitation sector but that is not well documented: women and girls in rural areas may be more likely to be attacked when they are collecting water or

looking for places to defecate in the open. Paid casual labor is also associated with feeling 3% less safe. The point estimates for safety for firewood collection, bathing/personal care, tending livestock, farming, and going to market are all negative but not statistically significant in our preferred model estimated on our main dataset. These coefficients are, however, statistically significant (and negative) in a model estimated using the larger set of ESM records (see Appendix C). Respondents were also more likely to report feeling unsafe when doing sports or hobbies, though this may be capturing a likelihood of sports-related injuries.

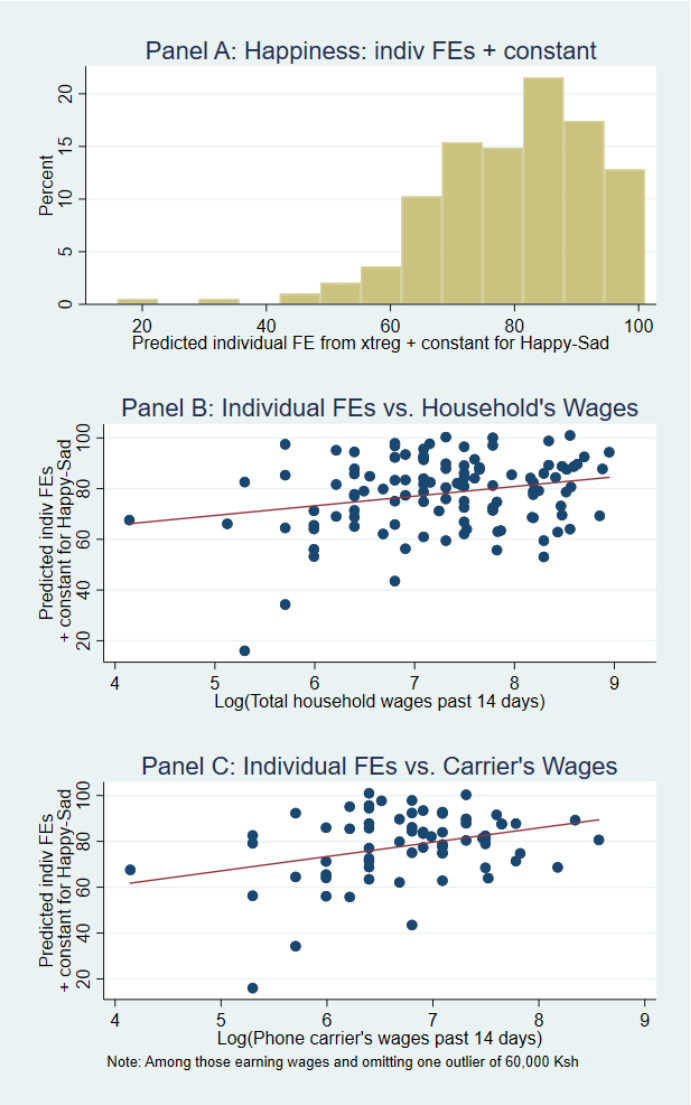
Figure 3: Coefficients from panel regression model of whether respondent felt "slight" or "severe" pain during the hour before the ESM survey

Notes: Coefficients plotted from panel regression model (xtlogit). Standard errors clustered at the person-level. Thicker line represents 95% confidence interval; thinner line 99%. N=8,560 records from n=162 individuals; 33 individuals dropped because there was no variation in their responses on pain.

Average happiness (person fixed effects)

We report here only the intercepts for the "happiness" measure; other results are available on request. Panel A of Figure 4 displays their distribution with the population-level intercept added to maintain a scale of 0-100. This represents the distribution of average momentary happiness in our study population of 195 individuals, the first such estimate we are aware of outside industrialized countries.

Figure 4. Predicted intercepts from Happy-Sad panel regression (Panel A), plotted against household's reported wages (Panel B) and the phone carrier's reported wages in the past two weeks (Panel C).



We employed a simple quadratic fit to explore relationship between the intercept and age and found neither coefficient was statistically different from zero. Kahneman et al. (2004) similarly found a low correlation with DRM data. We similarly found no statistically significant correlation between the intercept and education nor gender, though the latter is under-powered.

Following Kahneman and Deaton (2010), we use the log of three different income measures rather than its absolute amount because respondents are more likely to perceive

changes or differences in percentages rather than in absolute amounts. One notable difference in their study and ours, however, is that 40% of our households reported no earned income in the past two weeks, consistent with interviewing agricultural households during the dry, post-harvest season. The log operator converts these zeros to missing values, so our regressions should be interpreted as the effect of income on well-being *conditional* on earning some income. We also briefly discuss regressions using absolute values that do include these zero-wage households. The models also exclude one wage record of 60,000 Ksh (a monthly income of USD1,200), which is an order of magnitude higher than all other respondents. It is likely this income is misreported.

We find no statistically significant relationship between the intercepts and the log of the midpoint of a self-reported total monthly household income, asked in ranges (ie. 5,000 – 10,000 Ksh, 10,000 – 15,000 Ksh). We also find no statistically significant relationship with the log of a wealth index score creating using information from assets and housing characteristics with a Principal Components Analysis (PCA) approach (Filmer and Pritchett 2001).

We do find a statistically significant relationship with total household wages over the past 14 days, asked individually of each household member who worked for wages, and summed over all household members (Panel B, Figure 4). It is, however, very small in magnitude (β=3.81, t=2.69): our results imply that increasing household income by 10% increases the average happiness by only 0.36 units (3.81*log(1.1)) on the 0-100 scale. This relationship was also not statistically significant in a quadratic fit with the absolute level rather than its log.

We find a larger though still modest relationship between average momentary well-being and the total labor income earned over the past 2 weeks by the water carrier ONLY (Panel C of Figure 4, β=6.25, t=2.80). A total of 68 water carriers earned some labor income in the prior two weeks. Increasing wages by 10% increases average wellbeing by 0.60 units, twice the size of the effect of household wages. We also find a statistically significant relationship using the level rather than the log of carrier's wages. The relationship disappears when including the zero-wage-earning carriers. These relationships are robust to including data from the full set of ESM observations. We do not have information on each household member's perceived

bargaining power, but it seems logical that one's own earned wages contribute more to experienced well-being than wages earned by other household members if resources are not pooled completely. It could also be the case that even water carriers who pool their resources with the household feel a greater sense of contribution to family wealth as wages increase.

Conclusions

Overall, our results are consistent with those from similar studies in industrialized countries: respondents reported being less happy, less energetic, and less sociable when the ESM survey found them "at work" collecting water or firewood, farming, and performing casual or paid labor. Our results also highlight that these activities are also painful for many respondents. We also find evidence that our respondents, who were predominately women, felt more unsafe doing activities away from home. We find a small but statistically significant relationship between average hedonic well-being and the respondent's wages earned in the past two weeks, though not with annual household income or a constructed wealth index. We again caution readers that because our respondents were the household's main water carrier, our external validity could be limited if one believes there is non-random selection into water hauling.

A novel result to the momentary well-being literature suggests that entrepreneurs may be happier while at work. This result may help to bridge the evaluative/life satisfaction and hedonic well-being literatures if people are generally happier in the moment when they engage in work that they believe empowers them to live more productive lives with agency. While resource collection, wage labor or agricultural labor are all critical types of work for the family's economic wellbeing, entrepreneurs may consider their work both personally fulfilling and productive to their family's future. In the cross-country study of low-income countries described earlier, Reyes-García et al. (2016) finds that owning a business is associated with higher overall life satisfaction. Agency and the ability to control one's time and focus has also been associated with higher overall job satisfaction in the management literature (Fisher 2010).

Another novel result is that respondents' hedonic well-being is lower when they report "doing not much of anything". Such a category is not standard in most time use surveys and is not included in the UN's time use classification standard (UN Statistics Division 2016). As such

one should interpret it cautiously. The translation of the phrase is important, possibly including ideas of "resting" or "relaxing" (our Kimeru translation is provided in the appendix). We added it because prior experience in the study site suggested that many people seemed to have little productive work to do during the dry season. Our enumerators, in fact, tried to dissuade us from including it as a category since it would be perceived as socially unacceptable and lazy to admit having nothing to do. Given that our sample respondents were largely busy women doing work inside and outside the home, these results might well be stronger had we included a broader sample of the population including more men. Although economists are comfortable with the idea that the marginal utility of leisure is declining, our results suggest that at some point additional leisure time may provide disutility, perhaps from feelings of boredom or worthlessness. This again connects with the evaluative well-being literature, since seasonal idleness in agricultural regions is an analog to "unemployment" in formal labor markets in industrialized countries. Because we cannot classify subjects as "unemployed" based solely on whether they submitted ESM records with an activity of "nothing to do", we cannot explore whether the unemployed experience lower well-being in all activities, which Knabe et al. (2010) called the "saddening" effect. Goldsmith et al. (1996) find that current and past experiences of unemployment or inactivity reduce current self-esteem in the US. Clark et al. (2001) find "scarring" in the UK: higher spells of unemployment in the past are associated with lower evaluative well-being among those *currently* employed. Theodossiou (1998), using German data, find that the unemployed are 2.9 times more likely to think of themselves as a "worthless person".

Our results have policy implications for how we evaluate the changes to the living standards that would result from meeting the Sustainable Development Goals. Meeting many of these goals in rural areas of low-income countries will imply a reduction in time spent in the type of "work" explored in this article. SDG Target 7.b aims to "expand infrastructure…for supplying modern and sustainable energy services for all in developing countries", reducing biomass cooking and reducing fuelwood collection times. SDG Goal 6 similarly aims to bring water infrastructure closer to homes and reduce water collection times. Target 2.3 aims to "double the agricultural productivity and incomes of small-scale food producers", which is likely

to include increased mechanization of small-scale farming that will reduce manual farm labor. Target 5.4 is line with our focus on women's unpaid labor: to "recognize and value unpaid care and domestic work." The traditional benefit-cost approach to analyzing investments needed to meet the SDGs would involve putting a monetary value on the type of non-market work we explore here (Whittington and Cook 2019), such as time spent collecting firewood (Jeuland et al. 2021) or collecting water (Meeks 2017, Cook et al. 2016). Including information on how projects change the subjective well-being of participants, using either evaluative life satisfaction measures or changes in experienced utility, is an attractive complement to valuing time economically.

Declaration of interest statement

The authors declare no financial interests in this research.

Data and code availability

De-anonymized data were submitted to the Swedish National Data Service (SND) in 2019. We have not yet been assigned a DOI. We anticipate posting replication code (in Stata) to the same location.

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APPPENDICES for “Happy at work in Africa…”

Appendix A: Additional figures and tables
Appendix B: Additional details on sampling
Appendix C: Additional details on ESM data cleaning
Appendix D: Sensitivity analysis including larger set of “flagged” ESM observations

Appendix A: Additional figures and tables

Figure A 1. Age distribution of phone carriers

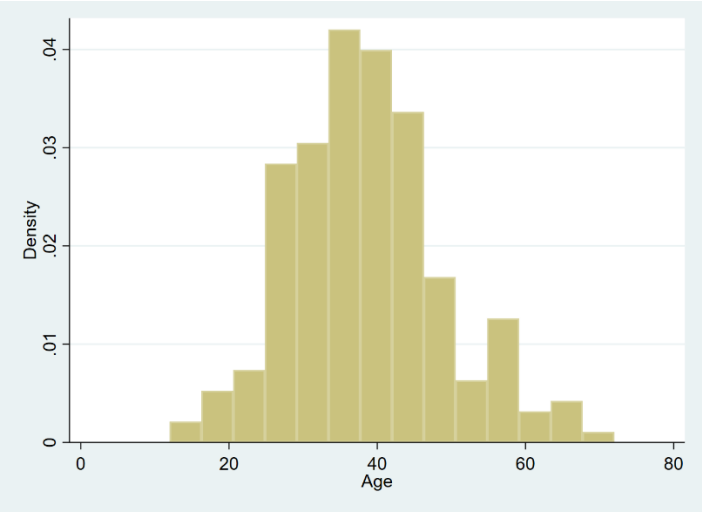

Table A 1. Panel (person fixed-effect) regressions on Happy-Sad (0-100) with and without controls for time of day and whether the respondent was alone.

	(1)	(2)	(3)	(4)
Attending meetings	0.95	0.87	1.17	1.10
	(0.90)	(0.83)	(1.10)	(1.01)
Collecting firewood	-3.49**	-3.50**	-3.15**	-3.18**
	(-2.31)	(-2.32)	(-2.04)	(-2.06)
Sleeping	-3.17**	-3.16**	-3.20**	-3.19**
	(-2.54)	(-2.53)	(-2.57)	(-2.56)
Studying	2.23	2.13	2.15	2.06
	(1.27)	(1.19)	(1.22)	(1.15)
Sports, hobbies	4.10*	4.04*	4.27*	4.22*
	(1.88)	(1.85)	(1.95)	(1.92)
Idle	-3.47*	-3.50*	-3.30*	-3.35*
	(-1.83)	(-1.86)	(-1.75)	(-1.79)
Bathing, Pers. Care	0.83	0.81	1.01	0.96
	(0.93)	(0.90)	(1.11)	(1.07)
Attending School	1.69	1.58	1.93	1.82
	(0.66)	(0.62)	(0.75)	(0.71)
Caring for others	-0.15	-0.21	-0.052	-0.11
	(-0.21)	(-0.28)	(-0.07)	(-0.15)
Radio or TV	-1.15	-1.16	-1.24	-1.23
	(-0.98)	(-0.98)	(-1.04)	(-1.04)
Socializing	-0.67	-0.78	-0.48	-0.59
	(-0.80)	(-0.92)	(-0.57)	(-0.69)
Collecting water	-6.92***	-6.91***	-6.71***	-6.72***
	(-7.31)	(-7.32)	(-6.85)	(-6.86)
Private	0.39	0.62	0.61	0.81
	(0.22)	(0.35)	(0.35)	(0.46)
Going to market	2.03**	1.99**	2.31***	2.27***
	(2.49)	(2.47)	(2.77)	(2.75)
Tending livestock	0.88	0.89	1.09	1.08
	(0.89)	(0.90)	(1.12)	(1.11)
Farming, own	-3.38***	-3.38***	-3.08***	-3.10***
	(-3.83)	(-3.79)	(-3.37)	(-3.38)
Casual labor, unpaid	-2.77	-2.83	-2.40	-2.48
	(-1.29)	(-1.31)	(-1.10)	(-1.14)
Casual labor, paid	-6.22***	-6.38***	-5.90***	-6.08***
	(-3.90)	(-4.11)	(-3.59)	(-3.79)
Paid formal labor	-9.49*	-9.54*	-9.24	-9.29
	(-1.67)	(-1.68)	(-1.63)	(-1.64)
Work in own business	1.05	0.38	1.27	0.61
	(0.43)	(0.16)	(0.52)	(0.25)
=1 if alone		-0.14		-0.086
		(-0.28)		(-0.16)
Afternoon (noon-5pm)			-0.50	-0.47
			(-0.94)	(-0.89)
Evening (after 5pm)			0.47	0.44
			(0.77)	(0.70)
Constant	80.4***	80.5***	80.3***	80.4***
	(267.65)	(220.30)	(172.30)	(143.36)
Observations	9469	9444	9469	9444

Notes: t-statistics in parentheses. * significant at 90%, **95%, ***99%.

Table A 2. Fixed-effect panel regressions of happiness, sociability, energy and safety.

	(1) Happy	(2) Sociable	(3) Energetic	(4) Safe
Attending meetings	1.10	0.28	2.63*	-0.47
	(1.01)	(0.20)	(1.73)	(-0.38)
Collecting firewood	-3.18**	-6.54***	-10.0***	-2.68
	(-2.06)	(-4.00)	(-7.63)	(-1.57)
Sleeping	-3.19**	-4.12**	3.18*	-1.87
	(-2.56)	(-2.15)	(1.82)	(-1.43)
Studying	2.06	-3.15	5.50**	-1.71
	(1.15)	(-1.07)	(2.22)	(-0.82)
Sports, hobbies	4.22*	3.80	-1.14	-9.19**
	(1.92)	(0.55)	(-0.15)	(-2.02)
Idle	-3.35*	-4.80**	1.28	-1.22
	(-1.79)	(-1.98)	(0.62)	(-0.65)
Bathing, Pers. Care	0.96	-2.47	0.74	-1.38
	(1.07)	(-1.56)	(0.49)	(-1.21)
Attending School	1.82	-2.85	-2.65	-3.02
	(0.71)	(-0.58)	(-0.89)	(-0.58)
Caring for others	-0.11	-0.57	-0.35	0.057
	(-0.15)	(-0.44)	(-0.23)	(0.06)
Radio or TV	-1.23	0.0038	3.84**	0.26
	(-1.04)	(0.00)	(2.16)	(0.16)
Socializing	-0.59	2.28*	2.66**	-0.57
	(-0.69)	(1.82)	(2.28)	(-0.69)
Collecting water	-6.72***	-2.32*	-11.5***	-3.29***
	(-6.86)	(-1.92)	(-8.04)	(-2.71)
Private	0.81	-8.45**	2.27	-1.63
	(0.46)	(-2.53)	(0.94)	(-0.79)
Going to market	2.27***	1.25	-1.27	0.31
	(2.75)	(0.76)	(-0.90)	(0.30)
Tending livestock	1.08	-1.67	-3.81***	-1.05
	(1.11)	(-1.08)	(-2.95)	(-0.90)
Farming, own	-3.10***	-3.97***	-12.9***	-1.22
	(-3.38)	(-2.80)	(-7.84)	(-1.33)
Casual labor, unpaid	-2.48	-4.31	-6.74***	0.58
	(-1.14)	(-1.63)	(-2.90)	(0.27)
Casual labor, paid	-6.08***	-1.67	-14.0***	-3.03*
	(-3.79)	(-0.93)	(-5.70)	(-1.68)
Paid formal labor	-9.29	-4.39	-8.48	-2.63
	(-1.64)	(-1.33)	(-1.52)	(-0.61)
Work in own business	0.61	2.93	0.42	-1.69
	(0.25)	(0.66)	(0.12)	(-0.63)
=1 if alone	-0.086	-11.2***	-1.87**	-0.88
	(-0.16)	(-8.39)	(-2.48)	(-1.46)
Afternoon (noon-5pm)	-0.47	1.71***	-8.10***	-0.47
	(-0.89)	(2.94)	(-9.08)	(-0.95)
Evening (after 5pm)	0.44	2.32***	-11.8***	0.30
	(0.70)	(2.74)	(-9.62)	(0.45)
Constant	80.4***	68.7***	46.7***	74.1***
	(143.36)	(82.49)	(51.28)	(125.86)
Observations	9444	9417	9433	9451

Notes: t-statistics in parentheses. * significant at 90%, **95%, ***99%.

Table A 3. Time Use Categories and Descriptions

Label (English)	Label (Kimeru)	Description (English)	Description (Kimeru)
Meetings	micemanio	Time spent attending community meetings, going to church, or attending funerals	Igiita riria utumaira gwita micemanione ya ntura, gwita kanicene kana gwita mathikone
Collecting firewood	Kuuna nku	Time spent collecting firewood. This includes the time spent walking from the house to the area where you collect and back.	Igiita riria utumaira kuuna nku, ugitaranagia, kagita karia utumaira kuuma njaa gweta naaria uunaa nku na gucoka njaa
Sleeping	Kumama	Time spent sleeping	Kagiita karia utumaira kumama
Other work outside the home	Ngugi ingi ome ya njaa	Time spent on other kinds of work or business outside the home, besides farming or caring for livestock.	Igiita riria utumaira kurita ngugi ingi kana biachara ome ya njaa iti kurima kana kumenyera nyomoo cia njaa
Reading and studying	kuthoma	Time spent reading books, newspapers, magazines or, for children, doing homework	Igiita riria utumaira kuthoma, mauku, gazeti, kana aana kubwithia ngugi iria baei cia cukuru
Games and hobbies	Michetho an matu yaria wendete	Time spent on games and fun activities or hobbies	igiita riria utumaira guchetha michetho na mantu yaria wendete/ yaria yakugwiragia.
Not much of anything	guti uu kuthithagia	Time spent doing not much of anything	Igiita riria utumaira utiu ukuthithia
Bathing	Kuthamba	Time spent bathing and washing your own body. If you wash a source away from the household, include the time spent walking there and back.	Igiita riria utumaria kuthamba, akethirwa uthambaira kuraja na njaa, utaranie kagita karia utumaira gwita na gucoka
School	Cukuru	For children, time spent at school	Kagiita karia aana batumaira cukuru
Caring for children and others	Kumenyera aana na bangi	Time spent caring for children, including breastfeeding, bathing children, dressing children, and helping them with their homework; and time spent caring for elders, the sick and the physically challenged who need your support	Igiita riria utumaira kumenyera twana, ugitaranagia gwonkia kubathambia, kubekira nguo, na kubatetheria kurita gungi cia cukuru, na igiita riria utumagira kumenyera antu bakuuru, aajie, baria bataukiri ni icunci bia mwiri, akiri, na ibakwenda, utenthio bwaku
Radio or TV	Kameme na TV	Time spent watching television or listening to the radio	Kagiita karia utumagira kwona TV kana kuthiukira kameme

Socializing	Kurianira na antu bangi	Time spent socializing and talking with friends and relatives, and time spent eating meals, including breakfast, lunch, and dinner. Do not include time spent preparing food.	Igiita riria utumaira, kurianiria na kwaranina na acore na antu benu, na kagita karia utumaria kuria biakuria, witaranagia biakuria bia rukiiri thaa mugwanja na biogoro, utigutarania kagita karia utumirite kuthuranira biakuria biu
Collecting water	Gutaa ruuji	Time spent collecting water, including the time spent walking from the house to the water source, the time spent waiting to fill the container, and the time spent walking home	Igiita riria utumagira gutaa ruuji, ugitaranagia kagita karia utumagira kuuma njaa gwita naaria utaaga ruuji, na kagita karia wetagira kujuria kiria ugutaa nakio na kagita karia utumagira gucoka njaa.
Private	Mantu ya witho	This category is for time you spend doing something else that is private for you and you do not want to tell us about. That is OK.	Kagiita karia utumaira kubuithia mantu ya witho kana mantu jaria utikwenda kwariria
Market	Thoko	Time spent traveling to the market and back, as well as time spent at the market	Igiita riria utumaira gwita thoko na gucoka, amwa na igiita riria utumaira thokone.
Livestock	Nyomoo cia njaa	Time spent taking animals to graze or drink	Igiita riria utumaira kurithia nyomoo cia njaa kana kunyuithia ruuji
Farming	Urimi	Time spent for farming work including plowing, sowing, weeding, harvesting, or hoeing. This include working on your own farm, or working on someone else's farm, either paid or unpaid.	Igiita riria utumaira urimine, ugitaranagia, gucimba, kuanda, kurimira, kana guketha. Ugitaranagia kurita ngugi muundene jwaku, kurita ngugi muundene jwa munti ungi ukiriawa kana utikuriwa
Household chores	Gwita ngugi cia njaa	Time spent on household chores, like preparing meals or tea, pounding grain or shelling beans, sweeping, washing dishes and utensils, washing clothes and tidying.	Igiita riria utumaira kurita ngugi cia njaa, ta kuthuranira biakuria na kuruga, gutira into ja mpempe, kana kuura mungau, kwegera, kuthambia into, kuura nguo na kutheria

Appendix B: Additional details on sampling

We targeted a total sample of 250 households in the four sub-locations. We began by targeting households which had participated in 2013 survey (chosen by a random transect approach in 2013) and met the following criteria:

- The main source of water for the household was not a source in the compound (i.e. private well) nor primarily vended water.
- Households should have school aged children (6-18 years) who do not attend a boarding school i.e. they go home every day after school and must be within the area of study.

Of the 387 households interviewed in 2013, 180 household met these criteria. All these households were visited. If a household was not at home during the first visit, the enumerators asked around about the household and tried a second time to contact the household. In total, 85 were recruited in the study from the 2013 sample frame, or 47% of the total 180.

This prompted recruitment of new households to reach the target sample size. The replacement was to be done within the same four sub-locations with the same recruitment criteria above. We constructed a census by asking the area sub-chiefs and village elders to list all the households within their sub-locations which met the criteria and were not among the households interviewed in 2013. This census included 218 households in the Nairiri location, 78 in the Machako location, 194 in Mutionjuri and 20 in Kianjai.

A systematic sampling was applied to the listed households where every second household in the list was recruited. Households would sometimes fall within the same compound (i.e. a shared common gate). In these cases, we randomly chose one of the households to be interviewed through choosing straws.

In total, we contacted 264 households who had not been interviewed in 2013. Of these, 187 households (71%) were recruited, and roughly in proportion to the census lists drawn up by the local leaders (see Table 1). Of the 77 households who were contacted but not recruited:

- Eleven respondents (4% of the total 264) were dropped because the main water collector was physically challenged (i.e. hearing and sight problems) in a way that would have made it impossible to complete the time use surveys, had insurmountable difficulties using a smart phone; had substance abuse problems; or did not, in fact, have school-aged children at home.
- 48 households (18%) refused to be interviewed, either because the household head would not allow the spouse or main water collector to participate, the parents of the main water collector refused to allow the child to be involved in the study, or because of other reasons. A significant fraction of refusals were due to rumors that the researchers were members of the Illuminati or were devil-worshipers.
- 15 households (6%) could not be contacted, though only after one attempt.

Sample frame

Sublocation	No. of households listed	No. of households recruited
Nairiri	218	95 (44%)
Machako	78	25 (32%)
Mutionjuri	194	46 (24%)
Kianjai	20	7 (35%)
Total	510	173

Appendix C: Additional details on cleaning ESM records

In this section we detail the steps taken to clean the ESM records. We faced several challenges and we provide this detail both for research transparency and to help guide future researchers who might be interested in implementing ESM using ODK. We begin by describing the challenges and then detail the procedure for dropping or flagging records.

First, there were a small number (29) ESM records in our data that could not be matched back to a specific phone or household using the phone's unique deviceid or SIM card serial number, which was stored in the ODK record.

Second, enumerators had concerns about the quality of data from 8 households, for example because of eyesight problems or mental health concerns.

Third, the research team themselves generated ESM records when we installed the ODK app on new phones for the first time, generating a test record to be sure the app was working. We similarly generated test ESM records when phones malfunctioned and needed to be returned to the team to have software re-installed. We also had enumerators run through the app as they explained the ESM program to respondents, again generating "false" ESM data. Unfortunately, we did not *ex ante* design a simple way to distinguish these test records from "real" ESM records in the program.

Fourth, in some cases the server assigned incorrect dates or times to database records for reasons we do not understand. For example, one record was time-stamped as beginning in October 2037 and ending in September 2016.

Fifth, as discussed in the main text, we drop ESM records where we had reason to believe another household member had taken the phone and was filling out the forms. This includes records with an incorrect "secret animal", which we use as a password.

We drop records from our analysis for the five reasons described above.

A sixth problem is that there are cases where the timing and length of ESM records suggest that the survey was not completed in the manner expected. Rather than drop these records, we flag them as potentially problematic. Ideally, the data record should show that an ESM took about 3-5 minutes , and then 3-4 hours (or overnight) before they are prompted to complete the next ESM survey. There are three behaviors that would complicate this picture.

A) the subject completes the survey but thinks it did not go through, and quickly completes another one. Start times will not be exactly the same, but very close together. Nearly all answers will be the same. Length of both entries will be short. One should keep the first record, though it should not matter since the records have the same main fields.

B) The subject starts an ESM, but then leaves the app to take a call or do something else. The entry is left uncompleted. The Randomly-Remind Me prompt goes off hours later to remind them to do the next entry, and they see they have the older entry uncompleted. They complete it, then start the second one. The second one will appear to have been completed just after the last one has been completed. But the first entry will have a very long completion time. We cannot know how much of the first entry was completed at the correct time and how much was completed later, based on recall. So the first entry should likely be deleted, but the second entry is likely OK.

C) The subject ignores the RRM requests and completes many ESM records at once, analogous to the stories from Cziksentmihalyi's earlier pager and logbook problem. This would be characterized by several ESM records in quick succession.

The table below details our data cleaning procedures. Although our anonymized data is available in the SND depository, the Stata code to implement these procedures runs on the de-anonymized data. The code itself is, however, available on request.

Description	**Records dropped**	**Total ESM records**
1. Initial total records	--	23,943
2. Drop all records from 8 households (3 control, 5 treatment) where enumerators had concerns about the quality of data from household	146	23,797
3. Drop record from Feb 2016 during testing in the U.S.	1	23,796
4. Drop records with implausible dates for both the “start” and “end” timestamp.	639	23,157
5. Drop records likely to be during programming or training		
a. Timestamp between 11pm and 5am. Phones were programmed at night, and users would never have been prompted to complete at those times.	430	22,727
b. Start date is on or before the date the phone was deployed to the household	794	21,933
c. Form started or completed on a Sunday. Users would not have been prompted to complete, and research team used Sundays to program phones.	635	21,298
6. Drop if record submitted after study ended in October 2016	72	21,226
7. Drop records with incorrect passwords		
a. Drop *all* records from 12 phones where the password was incorrect in >90 % of records.	1,264	19,962

b. Drop all remaining records with incorrect password	465	19,497
8. Drop records with the exact same start time (to the second) on the same phone (server problem)	4	19,493
9. **Flag, but not drop**, records that have long completion times, were completed in close proximity to other records, or where more than four per day were completed.		
a. Flag records with a length to complete > 15 minutes	Flag 3,548	
b. Also flag records that began within 60 minutes of the last ESM completed	Addt'l 3,208	
c. Also flag records from days where more than four ESMs were recorded.	Addt'l 2,773	
d. Also lag all records from 27 phones where more than 75% of its ESM records are flagged in a), b) or c) above.	Addt'l 405	
TOTAL RECORDS UNFLAGGED (main dataset) TOTAL RECORDS FLAGGED (adds for sensitivity sample) TOTAL RECORDS for "full" dataset	**N=9,959** 9,934 **N=19,493**	

Appendix D. Sensitivity analysis using larger set of ESM observations

The results reported in the main text are based on an analysis sample of n=9,959 ESM observations from 195 households. As described in Appendix C, an additional 9,934 ESM records were flagged as valid observations but potentially problematic because they a) took over 15 minutes to complete, b) were submitted by someone who had submitted more than four ESM records that day, c) were submitted within an hour of a prior ESM record, or d) came from a phone where more than 75% of all ESM records had been flagged.

It is possible that we were overly conservative in data cleaning. This appendix therefore presents results from the key analyses in the paper run on the "full" set of ESM that includes these flagged observations. The "full" dataset contains n=19,493 ESM observations from 220 households. Results from the paper ("main") are presented alongside results from the "full" dataset for ease of comparison.

Figure D1. Diagnostics: main dataset (n=9,559). Repeats Figure 1 in main paper

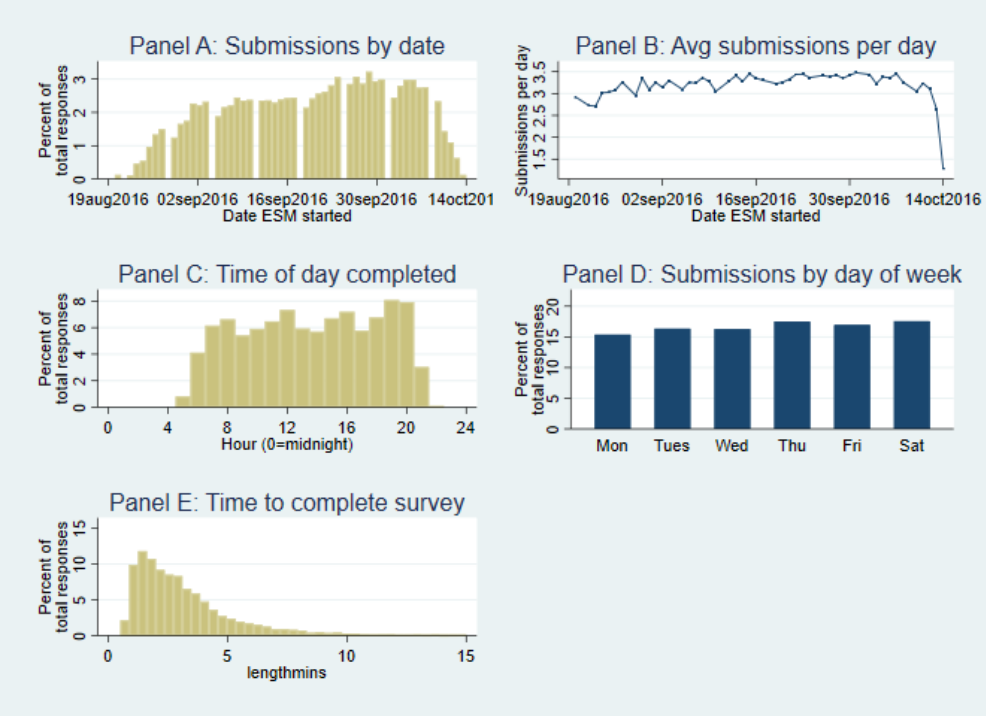

Figure D2. Diagnostics: full dataset (n=19,493)

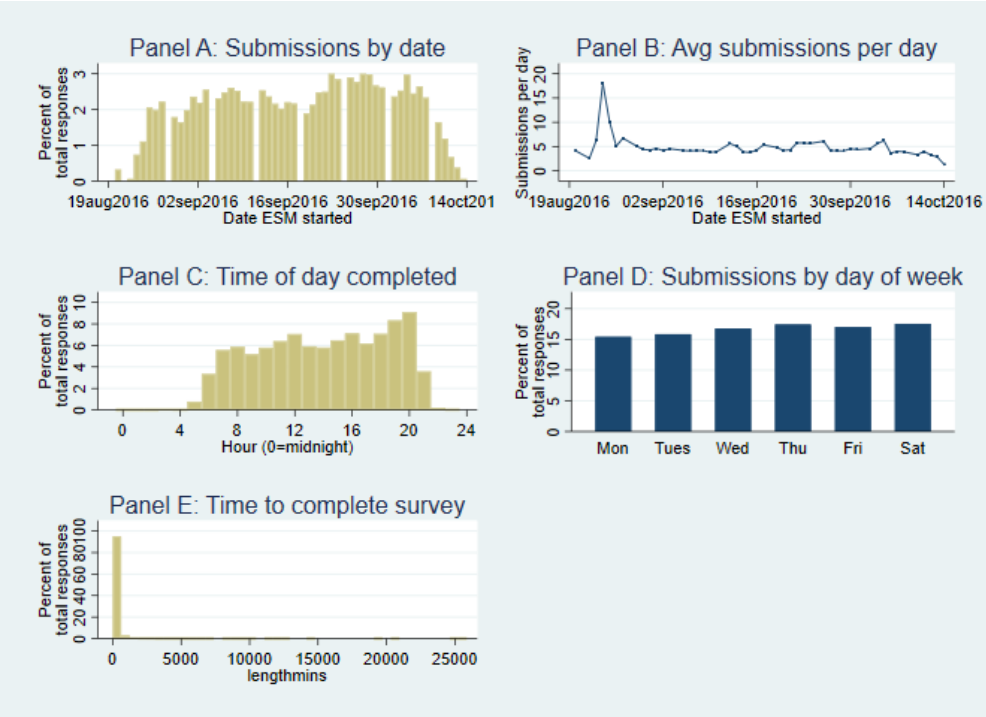

Table D1. Fixed-effects regression of happiness and sociability measures by activity: main vs. full sample (see table A2 in Appendix A)

	(1) Happy (main)	(2) Happy (full)	(3) Sociable (main)	(4) Sociable (full)
Attending meetings	1.10 (1.01)	1.37 (1.55)	0.28 (0.20)	0.40 (0.36)
Collecting firewood	-3.18** (-2.06)	-3.00** (-2.45)	-6.54*** (-4.00)	-6.03*** (-3.58)
Sleeping	-3.19** (-2.56)	-1.79** (-2.00)	-4.12** (-2.15)	-4.10*** (-2.89)
Studying	2.06 (1.15)	2.30* (1.79)	-3.15 (-1.07)	-2.52 (-1.23)
Sports, hobbies	4.22* (1.92)	1.24 (0.42)	3.80 (0.55)	-4.37 (-0.98)
Idle	-3.35* (-1.79)	-2.88** (-2.20)	-4.80** (-1.98)	-5.05*** (-3.16)
Bathing, Pers. Care	0.96 (1.07)	0.61 (0.72)	-2.47 (-1.56)	-1.09 (-0.86)
Attending School	1.82 (0.71)	2.55 (1.34)	-2.85 (-0.58)	-1.80 (-0.57)
Caring for others	-0.11 (-0.15)	0.13 (0.17)	-0.57 (-0.44)	-0.40 (-0.40)
Radio or TV	-1.23 (-1.04)	-1.04 (-1.25)	0.0038 (0.00)	-0.050 (-0.04)
Socializing	-0.59 (-0.69)	0.15 (0.24)	2.28* (1.82)	0.83 (0.98)
Collecting water	-6.72*** (-6.86)	-6.03*** (-7.62)	-2.32* (-1.92)	-3.35*** (-2.97)
Private	0.81 (0.46)	1.26 (0.89)	-8.45** (-2.53)	-5.96*** (-2.75)
Going to market	2.27*** (2.75)	2.47*** (3.24)	1.25 (0.76)	-0.16 (-0.13)
Tending livestock	1.08 (1.11)	0.20 (0.25)	-1.67 (-1.08)	-1.31 (-1.01)
Farming, own	-3.10*** (-3.38)	-2.59*** (-2.72)	-3.97*** (-2.80)	-3.75*** (-2.71)
Casual labor, unpaid	-2.48 (-1.14)	-5.41*** (-3.41)	-4.31 (-1.63)	-5.60*** (-3.26)
Casual labor, paid	-6.08*** (-3.79)	-5.74*** (-3.09)	-1.67 (-0.93)	-1.90 (-1.28)
Paid formal labor	-9.29 (-1.64)	-6.68 (-1.60)	-4.39 (-1.33)	-3.75 (-0.93)
Work in own business	0.61 (0.25)	3.74*** (2.74)	2.93 (0.66)	2.62 (0.71)
=1 if alone	-0.086 (-0.16)	-0.063 (-0.15)	-11.2*** (-8.39)	-9.39*** (-8.60)
Afternoon (noon-5pm)	-0.47 (-0.89)	-0.98** (-2.31)	1.71*** (2.94)	0.31 (0.62)
Evening (after 5pm)	0.44 (0.70)	0.036 (0.07)	2.32*** (2.74)	1.16** (1.97)
Constant	80.4*** (143.36)	80.6*** (171.79)	68.7*** (82.49)	68.9*** (93.94)
Observations	9444	19068	9417	19004

Table D2. Fixed-effects regression of energy and safety measures by activity: main vs. full sample (see table A2 in Appendix A)

	(1) Energetic (main)	(2) Energetic (full)	(3) Safe (main)	(4) Safe (full)
Attending meetings	2.63* (1.73)	3.73*** (3.46)	-0.47 (-0.38)	-1.66* (-1.73)
Collecting firewood	-10.0*** (-7.63)	-5.69*** (-4.70)	-2.68 (-1.57)	-5.19*** (-3.54)
Sleeping	3.18* (1.82)	2.46* (1.96)	-1.87 (-1.43)	-3.33*** (-3.34)
Studying	5.50** (2.22)	4.86*** (2.63)	-1.71 (-0.82)	-1.76 (-1.20)
Sports, hobbies	-1.14 (-0.15)	-1.81 (-0.41)	-9.19** (-2.02)	-5.29** (-2.49)
Idle	1.28 (0.62)	3.15* (1.80)	-1.22 (-0.65)	-1.51 (-1.18)
Bathing, Pers. Care	0.74 (0.49)	1.02 (0.82)	-1.38 (-1.21)	-2.51** (-2.28)
Attending School	-2.65 (-0.89)	-0.92 (-0.41)	-3.02 (-0.58)	-3.86 (-1.34)
Caring for others	-0.35 (-0.23)	0.90 (0.90)	0.057 (0.06)	-0.52 (-0.63)
Radio or TV	3.84** (2.16)	4.42*** (2.96)	0.26 (0.16)	-1.71 (-1.45)
Socializing	2.66** (2.28)	2.52*** (2.92)	-0.57 (-0.69)	-1.34** (-2.24)
Collecting water	-11.5*** (-8.04)	-9.32*** (-7.93)	-3.29*** (-2.71)	-3.39*** (-3.31)
Private	2.27 (0.94)	2.43* (1.72)	-1.63 (-0.79)	-3.23** (-2.54)
Going to market	-1.27 (-0.90)	-1.17 (-1.02)	0.31 (0.30)	-1.47* (-1.84)
Tending livestock	-3.81*** (-2.95)	-2.24** (-2.30)	-1.05 (-0.90)	-1.94** (-2.13)
Farming, own	-12.9*** (-7.84)	-10.7*** (-8.14)	-1.22 (-1.33)	-1.91** (-2.39)
Casual labor, unpaid	-6.74*** (-2.90)	-8.37*** (-4.17)	0.58 (0.27)	-4.78*** (-2.63)
Casual labor, paid	-14.0*** (-5.70)	-11.3*** (-6.42)	-3.03* (-1.68)	-3.12** (-2.48)
Paid formal labor	-8.48 (-1.52)	-6.97* (-1.94)	-2.63 (-0.61)	-4.12 (-0.83)
Work in own business	0.42 (0.12)	1.22 (0.53)	-1.69 (-0.63)	-4.12* (-1.68)
=1 if alone	-1.87** (-2.48)	-2.32*** (-4.01)	-0.88 (-1.46)	-0.83 (-1.58)
Afternoon (noon-5pm)	-8.10*** (-9.08)	-7.06*** (-10.41)	-0.47 (-0.95)	-0.51 (-1.28)
Evening (after 5pm)	-11.8*** (-9.62)	-9.64*** (-10.03)	0.30 (0.45)	-0.10 (-0.20)
Constant	46.7*** (51.28)	46.1*** (62.80)	74.1*** (125.86)	75.0*** (152.96)
Observations	9433	19017	9451	19119

Table D3. Fixed-effects regression of pain measure by activity: main vs. full sample (see table A2 in Appendix A)

	(1) Pain (main)	(2) Pain (full)
=1 if Slight or severe phys pain in last hour		
Attending meetings	-0.66*** (-4.05)	-0.52*** (-4.91)
Collecting firewood	0.76*** (4.03)	0.62*** (4.79)
Sleeping	0.091 (0.55)	0.0082 (0.07)
Studying	0.18 (0.66)	-0.22 (-1.11)
Sports, hobbies	1.32** (2.39)	0.45 (1.38)
Idle	-0.0030 (-0.01)	-0.26 (-1.45)
Bathing, Pers. Care	-0.15 (-0.85)	-0.15 (-1.23)
Attending School	0.65* (1.66)	0.12 (0.43)
Caring for others	0.021 (0.13)	-0.11 (-0.98)
Radio or TV	-0.24 (-1.13)	-0.21 (-1.40)
Socializing	-0.23* (-1.70)	-0.20** (-2.19)
Collecting water	1.37*** (12.38)	1.12*** (14.65)
Private	-0.32 (-1.04)	-0.040 (-0.23)
Going to market	0.17 (1.13)	0.098 (0.91)
Tending livestock	0.28* (1.70)	0.23* (1.93)
Farming, own	1.20*** (10.29)	0.95*** (11.57)
Casual labor, unpaid	0.53* (1.95)	0.74*** (4.17)
Casual labor, paid	1.10*** (5.63)	0.74*** (5.41)
Paid formal labor	0.62 (0.72)	-0.75 (-0.95)
Work in own business	0.53 (1.21)	0.30 (1.08)
=1 if alone	-0.044 (-0.64)	-0.17*** (-3.51)
Afternoon (noon-5pm)	0.35*** (4.70)	0.27*** (5.20)
Evening (after 5pm)	0.27*** (3.17)	0.18*** (3.12)
Observations	8560	18484

Figure D3. Predicted intercepts from Happy-Sad panel regression (Panel A), plotted against household's reported wages (Panel B) and the phone carrier's reported wages in the past two weeks (Panel C). Full sample (n=220, ESM n=19,493)