

# The well-being implications of women's time use

Sundus Saleemi<sup>1</sup>

## Abstract

In this paper, we estimate the impact of women's time use on their self-reported well-being based on evidence from women traders in markets in Ghana. We employ a novel dataset collected using a user-friendly Android application that records the time spent by the user in various activities in 24 hours. The user inputs an activity by clicking on an icon representing the activity they are engaged in. This time use data was input by users for at least five consecutive days. Moreover, we make use of the changes in patterns of women's time-use due to exogenous events, i.e. by exploring the variation between market and non-market days. "Market days" are specified days for markets in an area and experience heightened trading. At the close of each day, the user was also asked to record how they felt on a five-point scale from very sad to very happy. It is hypothesized that due to increased demands on women's time on market days, women experience negative emotions on market days. Moreover, the dataset allows for an assessment of the relationship between time spent in different activities (e.g., paid work, unpaid work, leisure) vis a vis its impact on individuals' self-reported well-being. The paper makes several contributions to existing and emerging literature on well-being and health, including mental health, and the impacts of the demands on women's time due to domestic and paid work. While it is documented that women spend more time in work compared to men, the impact of these time demands on women's well-being is less known. It also furthers the use of digital technologies to collect time-use data in time-pressed and financially constrained contexts in the Global South.

Keywords: Subjective well-being, time use, data methods

---

<sup>1</sup> Senior Researcher, Center for Development Research (ZEF), University of Bonn. Genscherallee 3, 53113, Bonn. Email: [ssaleemi@uni-bonn.de](mailto:ssaleemi@uni-bonn.de)

**Acknowledgements:** The author is immensely thankful to Dr Thomas Daum (University of Gothenburg) for sharing the code and graphics for the time-use app. Mark Muwanguzi (University of Pretoria) developed the time use app and patiently made required changes after several rounds of testing and piloting, my profound thanks are due to him. Data collection would not be possible without the research team at CSIR-STEPRI, Accra Ghana. I am grateful to Crystal Bubune Letsa, Johnny Owusu-Author, Abubakri Mohammed, Sylvia Baah-Tuahene, Marilyn Yeboah and Rose Omari. The author also thanks Dr Heike Baumüller and Prof Dr Joachim von Braun for their support. The paper is part of the research for the Program of Accompanying Research in Agricultural Innovations (PARI). PARI is supported by the German Federal Ministry for Economic Cooperation and Development (BMZ). All errors and omissions are my own.

## Introduction

The distribution of time spent on work and non-work activities is distinct for men and women. Globally, women undertake more work than men and are more likely to be time-burdened, i.e., having competing demands on their time (Charmes, 2019). Women's overall work includes cooking, cleaning, household maintenance, and care of children, the elderly and the sick members of the household. In many parts of the world, in rural areas and urban areas without infrastructure for the provisioning of water and energy, women are further responsible for collecting water and fuel for household use. Moreover, women make significant contributions to crops and livestock farming in staple and market agriculture. Additionally, women undertake non-farm employment, businesses and trade. Primarily, it is the combination of home production, largely unpaid, with work either on the farm, market or the workplace that leads to what is often referred to as the “double” burden of work.

The documentation of the differences in the time spent by women and men in various types of work has improved in recent years. While nationally representative time use data has been more consistently available for some industrialized economies, efforts are being made to make this data available for developing economies as well. Making this data available is salient as differences in men's and women's time use is a key dimension of gender inequality. However, the impact of women's time use on their well-being is less researched, notably, in the developing world (Dolan, Peasgood & White, 2008; Addai, Opoku-Agyeman, & Amanfu, 2014; Seymour & Floro, 2021). The reasons behind this relative scarcity of evidence are twofold – one, in many countries, collection and analyses of time-use data are still in their infancy. Second, assessment of the impact of patterns of time use on individual well-being is complicated by the changes accompanying changes in time use, i.e., an individual may increase the amount of time in work reducing their leisure. Still, the accompanying changes in the earned income make it difficult to separate the impact of changes in time use from changes in income.

This paper attempts to fill this gap in the literature; we assess the impact of changes in women's time use on their self-reported well-being in Ghana using primary data. To this end, we exploit the differences in the time women traders spend in the markets on two types of days called “market” and “non-market” days. In this way, differences in the time spent by women in different types of work and between overall work and leisure are due to an exogenous factor. We assess the impact of day type (market vs non-market day), time spent in total work, the distribution of time between paid and unpaid work and work and leisure on women's self-reported feelings on a particular day.

Two types of data were collected from women traders in the markets. First, survey data including time use, diets, household expenditure, and subjective well-being was collected from the women traders. Second, in a follow-up to the survey, an Android-based application was developed that allowed users to record their time use. The application uses pictures of various activities that a user can tap and the time spent in that particular activity is recorded (see appendix). The list of activities is based on the time-use module developed and tested in diverse contexts for the Women's Empowerment in Agriculture Index (WEAI, IFPRI)<sup>2</sup>. At the end of the day (20:00 every day) the user was asked, "How are you feeling today?". The user could report their mood by tapping on one of the five emojis displayed on the screen. These five emojis represent emotions ranging from very sad to very happy (see appendix). Self-reports on the same day can reduce the bias that may arise from the difference in the time of reports of a subjective indicator and an event. Indicators of subjective well-being may be more accurate closer they are to time and experience (Kahneman & Krueger, 2006). Mobile phones with the time tracking application were provided to traders to self-report their time use data and mood throughout the week. Since the week included both market and non-market days, we hypothesise that women traders are more likely to report negative emotions on market days compared to non-market days.

Women's double burden of work is primarily due to norms that assign them a disproportionate share of care and domestic work; women globally undertake a larger share of this work than men (Rathnayaka & Weerahewa, 2015; Seymour, Malapit & Quisumbing, 2020). In many developing countries, women's work is compounded by high fertility rates; large family size increases women's work at home. In these contexts, markets for goods and services that can substitute the output for women's work (cooked meals, paid childcare, elderly care) are also absent or underdeveloped. There is also low penetration of infrastructure and technologies (Grassi, Landberg & Huyer, 2015) shown to have reduced women's domestic work in Europe and North America such as electricity, access to piped water, and home appliances such as washing machines, dryers, vacuum cleaners and dishwashers (Greenwood, Seshadri & Yorukoglu, 2005). This double burden results in women having fewer hours per day for rest, self-care, leisure, hobbies and socializing – activities that potentially contribute to their well-being.

---

<sup>2</sup> Activities include 1. Sleeping and resting 2. Eating and drinking 3. Personal Care 4. School Work (incl homework) 5. Work as employed 6. Own business work 7. Farming/Livestock/Fishing 8. Shopping/getting services 9. Weaving/Sewing/Textile Care 10. Cooking 11. Domestic Work 12. Fetching wood/fuel 13. Fetching water 14. Care for Children/elderly/sick 15. Travelling and commuting 16. Watching TV/listening to radio/reading 17. Exercising 18. Social activities/hobbies 19. Religious Activities

In this paper, we assess the effect of women's time use on their subjective well-being using primary data collected from women traders in two markets in Ghana. These markets provide a setting to assess changes in self-reported well-being due to changes in time use. Traders in these markets work throughout the week. However, some days during the week are assigned as "market days" when more trading takes place. There are more sellers and buyers in the markets on market days, traders often spend more time in the market on these days compared to "non-market" days. Since the traders work throughout the week but are more time-burdened on market days, a comparison of their self-reported well-being on these two types of days can show the impact of time burdens on well-being.

## **Data and Methods**

We use primary data of women traders in two markets in Ghana. First, survey data was collected from 313 traders in two markets in the Greater Accra Metropolitan Area (AMA)<sup>3</sup>. This survey includes data on women's characteristics and information about their household including age, education, marital status, children, household expenditure and assets. Additionally, the survey included questions on women's time use and subjective well-being. Respondents to the survey were asked for their consent to participate in follow-up data collection. Out of the 313 respondents, 185 (60 percent) agreed to participate in the follow-up. Of the 185 who agreed, 60 participants were randomly selected for the follow-up<sup>4</sup>. The follow-up data was collected using an Android application designed to record data on the participants' time use and subjective well-being.

The follow-up was conducted in three phases, in the first phase 15 traders were provided Android phones with the time use app to record their time use and mood data. This batch recorded their data for a week between October 24<sup>th</sup>- Nov 3<sup>rd</sup>, 2023. A second batch of 15 traders were given the phones for the subsequent week and a third batch of 30 women were provided the phones from 25<sup>th</sup> Nov to December 03, 2023. During the week, participants received regular calls from the research team to remind them to record their data correctly and regularly. Moreover, very few participants recorded their mood data regularly in the first two batches, therefore, in the third batch an additional alarm was set on the mobile phones to remind participants to log in the mood data. The research teams visited each participant at least twice during the week. The phones were connected to the internet by the teams and the recorded data was synced to the cloud. The unique ID assigned to each of the respondents in the first survey

---

<sup>3</sup> The original survey was conducted in three markets, two in AMA and one market in the Bono East region. The follow-up was conducted only in the two markets in AMA.

<sup>4</sup> A smaller number were selected as the research budget was limited and the researchers could purchase only 30 new android phones for data collection.

was programmed into the application to enable the merging of the data received from the app with the survey data.

The Android application was designed to record the time in various activities throughout the day. The list includes 1. Sleeping and resting 2. Eating and drinking 3. Personal Care 4. School Work (incl homework) 5. Work as employed 6. Own business work 7. Farming/Livestock/Fishing 8. Shopping/getting services 9. Weaving/Sewing/Textile Care 10. Cooking 11. Domestic Work 12. Fetching wood/fuel 13. Fetching water 14. Care for Children/elderly/sick 15. Travelling and commuting 16. Watching TV/listening to radio/reading 17. Exercising 18. Social activities/hobbies 19. Religious Activities. The activities were represented pictorially; Daum et al (2019) pre-tested the pictorial representation of the activities in Zambia and the same graphics were used in this application (see examples of graphics in the appendix, Appendix Fig 1).

The application was self-administered by the respondent who logged in their time use for at least seven days using the app. The respondent clicked on the relevant picture to start recording her time on that activity and the time in seconds was automatically recorded by the app until another activity was clicked. Up to two activities could be simultaneously recorded. The respondents received regular reminders to log in their activities. At the end of each day, the app asked the respondents how they were feeling that day. The respondents could choose from five emojis shown on the screen that showed emotions ranging from very sad to very happy (see appendix for graphics, Appendix Fig 2). We use this data to estimate the impact of day type (market vs non-market day) on their self-reported well-being (1 = very sad, 2 = sad, 3 =neither happy nor sad, 4= happy and 5= very happy).

It is hypothesized that due to higher demands on time on market days, women are likely to report more negative (or less positive) responses on market days. We estimate the effect of day type on the respondent's reported feelings using the following equation:

$$SWB_{i,t} = \gamma_1 MarketDay_t + \gamma_2 Y_i + \gamma_3 X_t + \varepsilon_i \quad Eq (1)$$

Where,

$SWB_{i,t}$  = self-reported well-being of trader i, on day t [ 1 = very sad, 2 = sad, 3 =neither happy nor sad, 4= happy and 5= very happy]

$MarketDay_t$  = 1 if the day t was market day, 0 otherwise

$Y_i$  are characteristics of trader i including, age, marital status, education, number of children, number of household members, households' monthly expenditure per capita and household wealth quintile

$X_t$  = dummy variable for day t

Equation (1) is estimated using both Random Effects (RE) and Fixed Effects (FE) models for panel data. To estimate the FE models,  $Y_i$  is dropped as individual characteristics are time-invariant.  $X_t$  is added to both models are the conditions on a particular day, for example, the weather is expected to have a significant impact on the self-reports of all respondents.

To estimate the impact of the overall work we estimate equation (1) with the number of hours spent by a trader in total work (paid and unpaid). Paid work includes the time spent by the trader in their own business (trading in the market), time spent in wage employment (if any), time spent in farming (if any) and time spent in carrying goods to the market. Unpaid work includes domestic work, care work (care for the sick, children and the elderly in the household), and fetching fuel and water for household use. Leisure time includes time spent on hobbies and socializing, self-care and religious activities. As the time spent in one type of activity impacts that spent in another, each time variable is introduced sequentially. First, we include the total time in work as an explanatory variable. Then we disaggregate total work into paid and unpaid work. We also calculate the fraction of total work spent in paid and unpaid work to assess the effects of the distribution of overall work in different types. Data on women's characteristics including age, education, marital status, and children and household data including members, monthly expenditure, and assets from the survey are combined with the data collected via the app and added as control variables.

Equation (1) then takes the following form:

$$SWB_{i,t} = \gamma_1 Hours_{i,t} + \gamma_2 Y_i + \gamma_3 X_t + \varepsilon_i \quad Eq (1a)$$

Where

$Hours_{i,t}$  = hrs spent by a woman i on day t in 1) total work 2) paid work 3) unpaid work and 4) leisure

Total work hours = paid work + unpaid work

Paid work = time in own business, employment, farming and carrying goods

Unpaid work = time in domestic work, cooking, care work

Leisure hours = socialising, hobbies, religious activities and personal care

Table 1 below shows the summary statistics for all data and data disaggregated by market and non-market days. After cleaning the data<sup>5</sup> and keeping it for participants who logged in their time use consistently for at least 5 days during the week, we have a total of 325

---

<sup>5</sup> Some obviously wrong data were dropped, for example, if a respondent logged in an activity and continued it for over an entire day suggesting that she logged it and forgot to tap another activity. We kept data if the time spent in any activity (besides sleeping and resting) was under 16 hrs per day and if combined activities (such as unpaid work) was under 20 hrs.

observations from 57 respondents. The time spent by traders in total work (domestic and paid work) is significantly higher on market days than on non-market days. Women report spending on average 8.8 hours in work on market days compared to 7.8 hours on non-market days. A look at the categories of work shows that this difference is due to the difference in the time spent in paid work, predominantly working in their own business (trading) activities – women on average spend 6.5 hours in business activities on market days compared to 5.1 hours on non-market days.

*Table 1: Summary Statistics*

VARIABLES	(1) Overall mean (n=325)	(2) Market Day mean (n=90)	(3) Non-Market mean (n= 235)	(4) t -stat	(5) p
Total Work, hrs	8.0	8,8	7,8	-1,85	0,066
Paid Work, hrs	5.8	6,8	5,5	-2,40	0,017
Own Business Work, hrs	5.5	6,5	5,1	-2,43	0,016
Domestic Work, hrs	2.2	2,0	2,3	0,83	0,408
Leisure, hrs	2.6	2,1	2,7	1,82	0,070
<b>Respondent Characters</b>					
Respondent Age	37.4	37,8	37,3	-0,481	0,6309
Schooling	1.4	1,4	1,4	0,368	0,7134
Household Size	4.6	4,6	4,6	-0,046	0,9635
Days worked in the market	6.5	6,5	6,5	-0,280	0,7799
Household Monthly Expenditure, Cedi	4,060	4105,2	4042,2	-0,186	0,8528
Per per Monthly Expen, Cedi	991.5	1004,8	986,4	-0,224	0,8229
Number of Participant IDs	57	57	57		
<i>Note: Data kept for respondents with at least 5 days</i>					

There is a difference in the hours in domestic work on market and non-market days but the difference is not statistically significant. Traders’ reported time in leisure activities that include social and religious activities as well as time spent on hobbies is significantly less on market days than on non-market days suggesting that on market days women do not spend the time on domestic tasks but spend less time in leisure activities. There are no statistically significant differences in the respondents’ data on market and non-market days.

There are, however, a sizable number of missing data on the response to the question “How are you feeling today?”, our dependent variable. For respondents who logged this data but inconsistently, the response values are imputed– we replace the missing values with their median value on that day type (market or non-market day). For respondents who did not log their mood any day of the week, we drop them from our estimates. We are left with data from 27 respondents who logged in their time-use data for at least 5 days. The summary statistics of our sample are presented in Table 2 below disaggregated by market and non-market days. The data show patterns similar to those observed for the full sample; women spend significantly

more hours in work on market days than on non-market days and this difference is in the time they spend in paid work, primarily work in their own business.

Table 2: Summary Statistics of Estimation Sample

VARIABLES	(1) Market Day mean (n=41)	(2) Non-Market Day mean (n=116)	(3) diff	(4) t -stat	(5) p
Total Work, hrs	10.8	8.8	-2.69	0.008	10.8
Paid Work, hrs	8.3	6.3	-2.40	0.017	8.3
Own Business Work, hrs	7.7	6.0	-2.19	0.030	7.7
Domestic Work, hrs	2.6	2.5	-0.10	0.921	2.6
Leisure, hrs	2.6	3.2	1.15	0.253	2.6
Number of Participant IDs	27	27	27		

## Missing Data and Selection

As the users of the application did not consistently log in their response to the question, “How are you feeling today?”. We test if the missing data is non-random by estimating a panel Heckman selection model. The selection variable tested in the model is whether or not the respondent is literate, it is hypothesised that respondents who were unable to read the question “How are you feeling today?” and forgot the instructions from the training session were less likely to respond to it consistently throughout the week.

$$SWB_{i,t}^* = \gamma_1 Hours_{i,t} + v_{1,i} + \varepsilon_{i,t} \dots\dots\dots Equ (2)$$

$$SWB_{i,t} = SWB_{i,t}^* \text{ if } Mood Log = 1$$

$$SWB_{i,t} = \text{Not observed if } Mood Log = 0$$

The Selection Equation is:

$$Mood Log_{i,t} = \rho_1 Literate_i + v_{2,i} + \varepsilon_{i,t} \dots\dots\dots Equ (3)$$



## Results

Table 3 below shows the results of the estimation of equations (1) and (1a) using random and fixed effects models for panel data. The dependent variable is the response to the question, “How are you feeling today?” where the values of the responses range from 1, very sad to 5, very happy. In columns (1) and (2), the explanatory variable of interest is a binary indicator taking a value of 1 if the day of the mood log was a “market day” and zero otherwise. Column (1) shows the results of the random effects model (RE) and column (2) shows the estimates of the fixed effects model (FE). The RE estimates are controlled for the woman’s age, marital status, whether or not she has children, household expenditure per person (in the log) and the wealth quintile based on household assets. The estimates are further controlled for the day-fixed effects as the weather or other environmental factors on a particular day can potentially affect people’s emotional state. The coefficient of the indicator of a market day is not statistically significant; we do not find support for our hypothesis that traders experience negative emotions or less positive emotions on market days than on non-market days.

Columns (3) – (12) of Table 3 show the results of the estimation of Equation (1a) with hours of total work (columns 3 and 4), hours of paid work and unpaid work (columns 5 and 6), fraction of paid work in total work (columns 7 and 8), fraction of unpaid work in total work (columns 9 and 10) and hours in total work and leisure (columns 11 and 12) as main explanatory variables of interest. The RE estimates are again controlled for the trader’s age, marital status, whether or not she has children, household expenditure per person (in log), the wealth quintile based on household assets and day-fixed effects. The FE estimates include both individual fixed effects and day fixed effects.

As can be seen in Columns (3) and (4) the overall time spent in work in hours does not appear to significantly impact traders’ reported feelings on a particular day. This time spent in work disaggregated into paid and unpaid work suggests that traders experienced more positive emotions on days they spent more time in domestic work. This is shown by a positive coefficient of the time spent in domestic work that is statistically significant (Columns 5 and 6). The distribution of overall work hours appears to matter, as shown in columns (7) and (8). The coefficient of the fraction of total work spent in paid work has a negative impact on the respondents' stated feelings. The share of domestic work in total work hours, however, does not seem to significantly affect reported feelings (Columns 9 and 10).



Finally, the impact of time in hours spent in leisure activities is added as an explanatory variable in equation (1a). The results are shown in Columns (11 and 12). A statistically significant coefficient on the number of hours spent in leisure activities suggests a positive impact of leisure on respondents' stated feelings.

The estimates presented in Table 3 use data with imputed values of the dependent variable. As stated earlier, the respondents did not log their responses to the question, “How are you feeling today?” consistently throughout the week. We imputed the missing data by median values of their feelings for the day type. However, we estimated equations 1 and 1a without imputing this data as well, the results are presented in the appendix (Appendix Table 1). The results mirror the estimates with imputed data – the coefficient for market days is not statistically significant nor do we find a significant impact of total hours of work or paid work on women traders’ stated feelings on a particular day. The fraction of paid work in total work has a negative effect on the respondents’ stated mood that day and the hours spent in leisure has a positive effect.

### **Missing Data and Selection**

Table 4 below shows the estimates of the Heckman Selection Model. Estimates suggest that literate respondents are more likely to have logged in their responses to the question, “How are you feeling today?”. This is shown by a significant, positive coefficient of the binary indicator taking value 1 if the respondent can read and write in any language in the selection equation. The correlation of the error variances of the two equations suggests sample selection. The estimates of the impact of time spent in overall work, paid work, leisure and the fraction of time spent in paid work/business activities mirror the results of the estimated models without selection. The number of hours spent in leisure have a positive impact on the respondents’ reported feelings and the fraction of hours spent in paid work have a negative effect.

Table 4 Heckman Selection Model, Dependent Variable response to “How are you feeling today?”

EQUATION	VARIABLES	(1) Response	(2) Response	(3) Response	(4) Response
Value	Paid Work, hrs		0.00237 (0.0286)		
	Domestic Work, hrs		0.00396 (0.0299)		
	Leisure, hrs	0.108*** (0.0331)	0.107*** (0.0403)		
	Married/Cohabiting = 1	0.399 (0.321)	0.398 (0.303)	0.465 (0.375)	0.562 (0.375)
	Respondent has Children = 1, Yes	-1.427*** (0.303)	-1.428*** (0.317)	-1.269*** (0.353)	-1.262*** (0.334)
	Total Work, hrs	0.00277 (0.0248)			
	Time in Business/Total Work			-0.522** (0.227)	
	Time in Domestic/Total Work				0.420 (0.755)
Mood Log	Respondent Literacy = 1, Literate	0.524*** (0.169)	0.524*** (0.169)	0.525*** (0.168)	0.524*** (0.169)
	Corr (e.moodlog, e.response)	0.466*** (0.241)	0.561*** (0.200)	0.561** (0.292)	0.444 (0.290)
	Observations	168	168	168	168
	Number of Participant ID	27	27	27	27
	Controls	Yes	Yes	Yes	Yes
	Chi	93.17	104.7	97.16	92.87
	Selected	115	115	115	115

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Control Variables: Log of household expenditure per person, household wealth quintile, respondent age, day fixed effects.

## Discussion

In this paper, we attempt to evaluate the effect of women's time use on their self-reported well-being using primary data of women traders in markets in the Greater Accra Metropolitan Area in Ghana. These markets allow us to assess changes in self-reported well-being due to changes in patterns of women's time use. Women traders, who work in the markets throughout the week, dominate trade here. However, while trading takes place throughout the week, some days of the week are assigned as "market days". "Market days" are two to four days every week when trading activity is heightened and markets attract more buyers and sellers. Traders often spend more time in the market on these days compared to "non-market" days. Since the traders work throughout the week but are more time-burdened on market days, we compare the traders' self-reported well-being on these two types of days.

Moreover, we test if the time spent in overall work, paid and unpaid work and the distribution of time in different types of work impacts women's self-reported well-being. An Android phone-based application was designed to collect data on women traders' time use as well as their subjective well-being proxied by their response to the question, "How are you feeling today?". Respondents used the app for one week and logged in their time use and well-being data. We estimate RE and FE models for panel data employing this data to calculate the effect of market day on women's responses. Moreover, we estimate the impact of time spent in hours in overall work, paid work, unpaid work and leisure on

We do not find a significant effect of market days on women traders' stated feelings on a particular day. It can be conjectured that since market days are busier and more trading takes place on these days compared to non-market days, women traders earn higher incomes that offset any impact of higher time demands on these days. There is some indication that the higher time spent in business work as a fraction of overall work negatively impacts women traders' reported feelings, given that we do not find a significant impact of market days, it may be that on ordinary days greater time spent in business work without higher earnings hurts the traders' emotional state that day. Overall, we find that a greater number of hours spent in leisure activities have a positive impact on the women traders' stated feelings on a particular day.

The data collected for the paper was from an Android-based application that allowed respondents to record their data. Despite the pictorial representation of the various activities, regular reminders and visits from the research team, there were significant gaps in the data generated. Our analysis of the missing values of the data using the Heckman selection model suggests that literate respondents were more likely to consistently record their data. While

mobile phone-based data collection can provide more accurate time-use data, the applicability of these apps may still be limited in contexts with low levels of literacy and digital literacy. Future researchers looking to replicate the use of such apps for data collection may consider including more reminders and designing even more user-friendly applications for improved data quality.

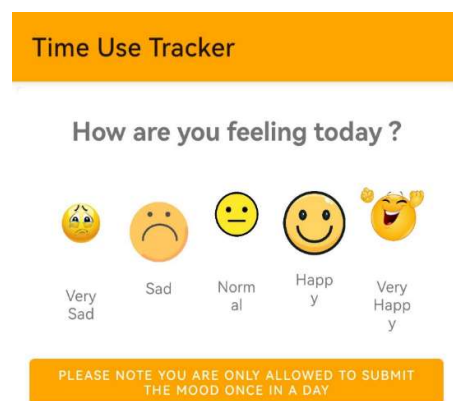
## References

- Addai, I., Opoku-Agyeman, C., & Amanfu, S. K. (2014). Exploring predictors of subjective well-being in Ghana: A micro-level study. *Journal of Happiness Studies*, 15, 869-890.
- Charmes, J. (2019). *The Unpaid Care Work and the Labour Market: An analysis of time use data based on the latest World Compilation of Time-use Surveys* (pp. 161-p). Geneva: ILO.
- Daum, T., Buchwald, H., Gerlicher, A., & Birner, R. (2019). Times Have Changed: Using a Pictorial Smartphone App to Collect Time–Use Data in Rural Zambia. *Field Methods*, 31(1), 3-22.
- Daum, T., Capezzone, F., & Birner, R. (2021). Using smartphone app collected data to explore the link between mechanization and intra-household allocation of time in Zambia. *Agriculture and Human Values*, 38, 411-429.
- Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of economic psychology*, 29(1), 94-122.
- Grassi, F., Landberg, J., & Huyer, S. (2015). Running out of time: The reduction of women's work burden in agricultural production. *Rome: Food and Agricultural Organization of the United Nations*.
- Greenwood, J., Seshadri, A., & Yorukoglu, M. (2005). Engines of liberation. *The Review of Economic Studies*, 72(1), 109-133.
- Kahneman, D., & Krueger, A. B. (2006). Developments in the measurement of subjective well-being. *Journal of Economic perspectives*, 20(1), 3-24.
- Rathnayaka, R. M. S. D., & Weerahewa, J. (2015). An analysis of gender differences in intra-household time allocation of rural farm families in Sri Lanka.
- Ruggeri, K., Garcia-Garzon, E., Maguire, Á., Matz, S., & Huppert, F. A. (2020). Well-being is more than happiness and life satisfaction: a multidimensional analysis of 21 countries. *Health and quality of life outcomes*, 18(1), 1-16.
- Seymour, G., & Floro, M. S. (2021). Signs of change: evidence on women's time use, identity, and subjective well-being in rural bangladesh. *Journal of Gender, Agriculture and Food Security*, 6(01), 1-17.
- Seymour, G., Malapit, H., & Quisumbing, A. (2020). Measuring time use in developing country agriculture: Evidence from Bangladesh and Uganda. *Feminist Economics*, 26(3), 169-199.
- Women's Empowerment in Agriculture Index (WEAI), International Food Policy Research Institute (IFPRI) <https://weai.ifpri.info/about-weai/>

## Appendix



Appendix Fig 1: Pictorial Representation of various activities in the Time Use Application



Appendix Fig 2: Screenshot of Time Use App, "How are you feeling today?"



*Appendix Table 1: Dependent Variable, Response to the question "How are you feeling today?" 1 very sad - 5 very happy.*

VARIABLES	(1) RE	(2) FE	(3) RE	(4) FE	(5) RE	(6) FE	(7) RE	(8) FE	(9) RE	(10) FE	(11) RE	(12) FE
Married/Cohabiting = 1	0.657* (0.379)		0.598* (0.360)		0.498 (0.377)				0.629* (0.381)		0.454 (0.339)	
Respondent has Children = 1, Yes	-1.119** (0.537)		-1.046** (0.527)		-1.072* (0.593)				-1.117** (0.551)		-1.221** (0.513)	
Market day = 1	0.188 (0.182)	0.193 (0.184)										
Total Work, hrs			-0.0283 (0.0256)	-0.0168 (0.0272)							0.00372 (0.0255)	0.00849 (0.0300)
Paid Work, hrs					-0.0351 (0.0256)	-0.0273 (0.0244)						
Domestic Work, hrs					0.0199 (0.0232)	0.0627** (0.0228)						
Time in Business/Total Work							-0.620** (0.252)	-0.534** (0.241)				
Time in Domestic/Total Work									0.474 (0.875)	0.619 (0.906)		
Leisure, hrs											0.0968** * (0.0328)	0.0735* (0.0395)
Observations	115	115	115	115	115	115	115	115	115	115	115	115
R-squared		0.012		0.007		0.070	0.070			0.011		0.041
Number of Participant ID	27	27	27	27	27	27	27	27	27	27	27	27
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1