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Does it matter who you ask for time-use data?

Deepti Sharma,[1] Hema Swaminathan,[2] and Rahul Lahoti[3]

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Abstract: Time-use statistics are sensitive to measurement error, especially errors that might be introduced based on whether the informant is reporting on herself or reporting on others in the household. In this paper, we use the nationally representative time-use survey in India and propensity score matching methods to investigate how self- and proxy reporting impact the reported time spent on various activities by men and women. Theoretically, we examine the mechanisms underpinning the differences in reporting and empirically test our hypothesis. Proxy informants tend to report higher time use for both men and women on employment activities (14–26 per cent) and lower time use on production for self-consumption, unpaid domestic work, and care work (5–33 per cent) as compared to self-reports. On average, female proxies differ more from self-reports when reporting about both men and women in their households as compared to male proxies. Investigating the mechanisms, we find that the self–proxy differences are not due to random error but are systemic. Information asymmetry between the self and proxy respondents plays a key role—spouses and self–proxy respondents with similar characteristics have smaller reporting differences than non-spouses and other respondents. Gendered perception of what activities are classified as work also play a key role in the differences.

Key words: time use, measurement error, gender

JEL classification: J22, J16, C83, C81

[1] Indian Institute of Management, Bangalore, India; [2] Economic Research and Development Impact, Asian Development Bank, Manila, Philippines and Centre for Public Policy, Indian Institute of Management, Bangalore, India [3] UNU-WIDER, Helsinki, Finland; corresponding author: rahul.lahoti@wider.unu.edu

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Katajanokanlaituri 6 B, 00160 Helsinki, Finland

1 Introduction

Knowing how individuals spend their time and how employment and household responsibilities are shared between men and women is key to comprehensively understanding the functioning of an economy and society. It is also critical to the understanding of gender dynamics and inequality in society (Hirway 2010). Time-use surveys (TUS) collect detailed and specific information on an individual's activities, which is not achieved by any other type of survey (Gershuny 2011). In our focus country, India, a nationally representative TUS was completed for the first time in 2019. During the past 20 years India has undergone rapid urbanization and population and economic growth (Fletcher et al. 2017). This period also coincides with a sharp decline in female labour force participation (from 31 to 21 per cent between 1998 and 2019) (Afridi et al. 2018; Klasen and Pieters 2015; Lahoti and Swaminathan 2016). Few studies have found demographic factors (caste, education, family status, childcare) and gender norms as determining factors in the reduction in female autonomy and labour force participation in India (Deshpande and Kabeer 2024; Eswaran et al. 2013; Gautham 2022; Gupta and Negi 2021); however, participation is different to time spent in various activities. TUS provide a more granular understanding of how individuals spend their time. Thus, the availability of time-use statistics can also help show how women distribute their time in productive and income-generating activities (Fletcher et al. 2017; Hirway and Jose 2011; Li 2023).

Collecting time-use data is time-consuming, recall intensive, and expensive (Buvinic and King 2018). Time-use data is difficult to collect in developing countries because there are many unstructured and marginal activities that tend to be carried out simultaneously (Esquivel et al. 2008; Irani and Vemireddy 2021). Additionally, several studies have raised methodological issues in time-use measurements, such as the collection method (direct observation, time diary method, interview method, or stylized questions method), categorization of activities, and harmonization of time use (Field et al. 2023; Hirway 2021; Kan 2008). However, measurement error in time-use reporting due to choice of respondent has rarely been investigated. Decisions on who to interview and what to ask can significantly affect the results of economic evaluations and stylized facts of development (De Weerdt et al. 2020).

The impact of informant identity on survey statistics has been studied in different contexts, but not in collecting time-use data. The difference in reporting by self- and proxy respondents has been studied in agricultural statistics (Dillon and Mensah 2023), income (Chen and Collins 2014), labour market participation (Abraham et al. 2023; Bardasi et al. 2011), wages (Reynolds and Wenger 2012), and asset ownership (Ambler et al. 2021; Deere et al. 2012; Fisher et al. 2010; Kilic et al. 2021). Using experimental and non-experimental methods, the literature has shown that measurement error due to the informant's identity is large. However, understanding whether and how the informant's identity impacts reporting of time use has rarely been undertaken. Most household surveys ask a single respondent from the household to report on time use for others in the household. The existence of information asymmetry, differential gender roles, and norms might lead to biases in reporting based on the choice of respondent (Dillon and Mensah 2023). The effect of gendered roles and norms (regressive or progressive) can impact the division of work within the household and, thereby, affect time spent in paid and unpaid work. Additionally, it can affect the time use reported; due to regressive societal gender norms, men may feel that performing and reporting time use for a particular job diminishes their status (Campaña et al. 2018) and they thus might provide politically correct answers by under-reporting their contribution to household chores. Furthermore, due to the simultaneity of work, it is difficult to disentangle women's time spent in household chores and paid work (e.g. self-employment, farm labour). Thus, there is often an invisibility to women's contributions to various activities, and the choice of respondent may exacerbate sensitivity in time-use data collection.

In this paper, we investigate whether the identity of the survey informant impacts the reported time use for an individual using a nationally representative TUS in India. In particular, we examine if self-reports

on time spent are systematically different than proxy reports for men and women for employment, household production, household work, and care activities. We present a theoretical framework to understand the mechanisms behind these self–proxy reporting differences. To test the framework empirically, we study whether reporting differences by self and proxy vary by characteristics of the proxy, such as gender, relationship to the informant, occupation, etc., and gender norms. Extensive tests are conducted to explore the heterogeneity and robustness of the results.

We use the first nationally representative TUS conducted in 2019 in India to investigate the impact of informant identity. The TUS interviewed 138,799 households across India and collected detailed information using the time diary approach on the previous day for 447,250 individuals aged six years and above. We focus on reporting differences in four major activities—employment, production for self-consumption, unpaid domestic work, and unpaid care work—in the working-age population (15–64 years of age).

The TUS was supposed to interview all household members on whom time-use information was collected and obtain information directly from them. However, in 36 per cent of the cases, individuals were not available to report on their time use, and other household members responded on their behalf (proxy). We use this variation in the informant identity to estimate the impact of the respondent's identity (self or proxy, gender, relationship to the individual, etc.) on the reported time use.

The choice of respondent for the survey is not random and depends on their availability: individuals who self-report systematically differ from those reported by a proxy. This could create systematic bias in our estimates (Abay et al. 2023). Hence, we employ multiple matching techniques to match the characteristics of a self-reported individual with those of a proxy-reported individual. The difference between the time reported by the matched pair gives us an estimate of the impact of the respondent identity on reporting.

We find large systematic differences between self- and proxy-reported time use across activities. Proxy informants tend to report higher time use for both men and women on employment activities (12–21 per cent) and lower time use on production for self-consumption, unpaid domestic work, and care work (5–33 per cent) as compared to self-reports. The absolute and relative differences vary by the gender of the person being reported on. For employment activities proxy estimates relative to self estimates are far higher for women than for men (21 vs 12 per cent), whereas for production of self-consumption and unpaid domestic work it is the reverse (4–9 per cent vs 22–28 per cent). The gender identity of the proxy also has an impact on reporting. When women proxy for men and other women, their estimates are likely to show greater divergence from self-reports than when men are proxies.

These results are robust across the various estimators—OLS, PSM, and IPW—model specifications, and matching methods. Following Oster (2019), we show that our results are also robust to a sufficiently high degree of selection on non-observables.

We present a theoretical framework to understand the channels for the differences in self–proxy reporting and then test several of these mechanisms using data. Random measurement error, asymmetric measurement error, and asymmetric information are the three broad reasons for the measurement error due to the choice of respondent (Ambler et al. 2021). We show that random measurement error is not the only source of error as the differences in reporting vary by both the sex of the proxy and the sex of the person being reported on. There are variations in differences in self–proxy reporting by type of activity and across households with differential gender norms, indicating that asymmetric measurement error also plays a role. Reporting differences when reporting on spouses vs non-spouses and when reporting on people with similar vs different characteristics suggest that asymmetric information is one of the mechanisms for the differences. When men report about their spouses, the self–proxy differences are far smaller than when they report about other women in the household. Also, when the charac-

teristics of the proxy and the person being reported on are similar (same employment sector or same age band), the self–proxy differences are lower than when the characteristics are different. Spouses or people with the same features are less likely to intentionally or unintentionally hide activities, and so will have less asymmetric information than other cases. We also perform heterogeneity tests by social groups, rural/urban status, class, and regions within the country.

Our paper contributes to different strands of the literature. First, we contribute to the growing literature on survey methodology that deals with understanding whether interviewing one or multiple members of the household matters. Our results suggest that measurement error in time-use reporting is non-random and systematic, and interviewing various members is critical to reducing this error. Most studies that investigate this in income, asset, or labour market contexts are based on small experimental samples (Fiala and Masselus 2022; Field et al. 2023; Kilic and Sohnesen 2019). Our paper is based on a nationally representative survey, and we can explore the various mechanisms underlying this error in depth.

Second, we show that measurement error arising from selection of respondents is strongly associated with demographic factors. Importantly, our study shows that the respondent's gender has a high influence on the perception of the household division of labour between men and women. Matching on factors such as marital status (spouse and non-spouse), gender norms, and rural and urban welfare levels also explains variation in the time use reported by self and proxy.

We discuss measurement error and related literature in Section 2. The description of the data and the analytical sample is given in Section 4, followed by methodology in Section 5. We present our descriptive and main results in Sections 6 and 7. In addition, heterogeneity analysis and robustness checks are shown in Sections 9 and 10, and a summary of the findings is presented in Section 11.

2 Literature

2.1 Time-use data

The availability of time-use data at the household level brings an important perspective in understanding the division of labour especially for women (including the extent of unpaid household labour) (Gupta and Negi 2021), dynamics of gender inequality (Brunnich et al. 2005; Gimenez-Nadal and Molina 2014; Hasanbasri et al. 2021; Irani and Vemireddy 2021; Srivastava 2020), and time poverty (Giurge et al. 2020; Kes and Swaminathan 2006). In addition to these issues, information on nutritional intake, ownership of assets, and income can be captured using TUS. Most studies can do so because of a shorter recall period bias (generally the previous day) and comprehensive information on all activities rather than a few selective ones (Frazis and Stewart 2012).

Studies have used Indian time-use data to estimate market work hours over the traditional labour force survey (Hirway and Jose 2011), to capture maternal childcare specifically in rural areas (Gautham 2022), and to test gender norms and the bargaining power nexus. A recent study by Li (2023) presents patterns of the changes (using the 1998 pilot and 2019 survey) in time-use patterns among men and women in urban and rural India. The study suggests there is a defeminization of rural labour force participation, as time spent in paid work has decreased for women; however, it remains mostly unchanged in urban areas. Despite these changes, the double burden of unpaid domestic work largely remains gendered, where women's time spent remains higher than men's in India (Rao and Raju 2020; Ratheesh and Anitha 2022; Srija and Vijay 2020).

Several studies have highlighted that time-use data collection is expensive and complex in nature, and the design of the survey is complex and has to be interlinked with other socio-demographic information—which is often weak in TUS (Esquivel et al. 2008; Finlay et al. 2019; Hirway 2021; Seymour et al.

2020). Using an experimental setup, Field et al. (2023) examine the collection of time-use data in the Indian context using a hybrid module, an enumerator-assisted method for time-use data collection. They find that the hybrid module is better than the stylized survey-based method or time diary approach, as it is less costly, quicker to train and administer, and, specifically for this case, appropriate for the less educated population in India.

2.2 Self vs proxy reporting in household surveys

The difference in reporting by self- and proxy respondents has been studied in agricultural statistics (Dillon and Mensah 2023), income (Chen and Collins 2014), labour market participation (Bardasi et al. 2011), wages (Reynolds and Wenger 2012), and asset ownership (Ambler et al. 2021; Deere et al. 2012; Fisher et al. 2010; Kilic et al. 2021). Using experimental and non-experimental methods, the literature has shown that measurement error due to the informant's identity is large. In this section we discuss some of these studies.

In the domain of measuring employment, studies have shown significant differences in self–proxy reporting. Kilic et al. (2022) shows evidence from two parallel national surveys conducted in Malawi that the standard 'business-as-usual' approach of using proxy respondents and non-private/group interviews results in significant under-reporting of employment, with stronger effects for self-employment. They find that under-reporting is linked to household wealth, proxy reporting, and potential complexities with interpreting/responding to questions on household non-farm operations. In a recent study, Dervisevic and Goldstein (2023) focus on identifying potential contributors to systemic discrepancies between self- and proxy reporting on labour outcomes and find that reporting is affected at a significant margin by both gender and marital satisfaction. Using a randomized experiment, Bardasi et al. (2011) do not find any difference in female participation due to informant type; however, a proxy respondent reports lower employment rates for males (particularly for agriculture).

In the domain of measuring earnings, the results are mixed. Tamborini and Kim (2013) find that regardless of the gender of the target respondent, proxies do not significantly skew earnings measurements for married workers. On the other hand, Fisher et al. (2010) find husband and wife education as an important factor behind the under-reporting of income specifically for wives. A cross-couple study by Chen and Collins (2014) to capture income and spending behaviour finds asymmetric information as an underlying reason for discrepancies in responses by self and proxy. Reynolds and Wenger (2012) highlight the differences in wage reporting due to informant type, which exacerbates the gender pay gap using the current population survey. Using matching methods similar to our study, they find self-reports of higher wages than proxy reports even after controlling for time-invariant characteristics.

In the domain of agricultural outcomes, Dillon and Mensah (2023) use a randomized control trial in Burkina Faso and find no respondent-type effects in the total area held by the family. However, the area farmed by random proxy reports differs significantly from self-reported land data. The implications of measurement error arising from a headship analysis compared to gendered analysis in the estimation of asset ownership are discussed by Deere et al. (2012) and Doss et al. (2018). These studies highlight the issue of collecting responses only from a male head of household (HoH) to be problematic as it gives an uni-directional reaction to a household's economic well-being compared to an integrated response of both males and females.

Though reporting differences between self- and proxy respondents have been studied in various domains, to our knowledge its impact on collecting time-use data has not been explored. We investigate that aspect in this study.

3 Theoretical framework

Household surveys aim to collect accurate data by observing or eliciting responses from individuals within the household. However, measurement error, which represents the discrepancy between the actual, unknown value of the collected characteristic and the recorded survey response, is an inherent challenge in this process (Dillon and Mensah 2023; Hirway 2021). Various sources contribute to measurement error, including the respondents themselves, questionnaire design, data collection methods, and interviewers (Groves 2005). In this study, we specifically investigate the measurement error resulting from selection of respondents.

Measurement errors can arise when respondents provide inaccurate responses. Factors such as selection criteria of respondents within the household, question complexity, social desirability bias, recall period, and telescoping can influence measurement error driven by respondents (Charmes 2021; Dervisevic and Goldstein 2023). In this study, we focus on understanding the discrepancies between self-reported and proxy-reported time use for different household members. We present testable predictions and propose several analytical approaches to differentiate among various explanations. Our theoretical framework is derived from the work of Ambler et al. (2021), who examined disagreements between spouses on matters of asset ownership and household decision-making. These disagreements can be broadly classified into three categories: random measurement error, asymmetric measurement error, and asymmetric information.

3.1 Random measurement error

Random measurement error pertains to discrepancies between self- and proxy reports that are unrelated to individual or household attributes and do not systematically differ between self and proxy. Such errors may arise due to enumerator characteristics (Rodriguez-Segura and Schueler 2023), rushed responses (Jeong et al. 2023), or misunderstandings of the questions. In the presence of random measurement error, systematic differences between self- and proxy responses are not expected.

In random measurement error, the probability of the proxy under-reporting or over-reporting the time spent compared to the self-reported time use is identical. Moreover, this probability of random error remains unaffected by the gender of the proxy, the individual being reported on, or any other characteristics of the self or proxy.

PREDICTION 1: If the random measurement error is the sole factor driving differences in reporting, then, on average, there should be no significant differences between self- and proxy reports, as any proxy under-reporting and over-reporting would exactly cancel out.

3.2 Asymmetric measurement error

Asymmetric measurement error results in responses systematically differing by the gender of the proxy and the gender of the individual being reported on. Here, the proxy is assumed to possess complete information regarding the time use of the individual they are reporting on, but errors arise due to differences in perceptions of time spent and differential gender norms-based reporting.

One aspect contributing to asymmetric measurement error is the differing perceptions of time spent on activities performed by men and women. For example, women might consider time spent taking care of livestock as a work-related activity. In contrast, men may classify it as household work, given the proximity of livestock to the residential compound. An activity in which women simultaneously care for children and watch television might be classified differently by self and proxy. A woman might classify it as mostly childcare, whereas the proxy might classify it as leisure.

Another influential factor is differential social norms that assign specific gender roles, impacting reporting by sex. While men and women may not strictly adhere to these prescribed roles, their proxies may report in line with societal norms, for various reasons. For instance, reporting women's time spent on employment activities by men might be influenced by perceived social censure associated with certain activities. Smaller reporting differences are expected in activities like household work, where gender norms are deeply entrenched and universally ascribe this responsibility to women. In contrast, in activities such as women's employment, where gender norms are more contested, more significant differences between self- and proxy reporting are anticipated. Additionally, social groups with more conservative gender norms, such as upper castes compared to Scheduled Castes/Scheduled Tribes (SC/ST) groups, are likely to exhibit higher discrepancies between self- and proxy reports.

Gender norms also dictate and influence the bargaining power of women in households (Mabsout and Van Staveren 2010). Women's bargaining power within a household refers to the ability of women to influence decision-making processes and outcomes in the domestic spheres (Doss 2013; Majlesi 2016). With higher bargaining power women will have more say in resource allocation, division of labour, financial choices, and other household-related decisions. In this sense, higher bargaining power promotes a better understanding of time allocation, which can reduce the differences in reporting between self or proxy.

PREDICTION 2: When asymmetric measurement error is present, reporting differences by the gender of the proxy emerge. As the probabilities of disagreements vary, we anticipate variations in disagreements across activities due to differences in the interpretation of time spent on different activities and the associated gender norms.

3.3 Asymmetric information error

Asymmetric information error arises from disparities in the information available to proxies concerning the activities of other individuals within the household. This discrepancy may occur as individuals strategically conceal information about their activities from one another to maintain income privacy or to avoid censure for deviating from social norms. Additionally, unintentional information asymmetry can occur due to observational limitations, where the proxy might not have full knowledge of the daily activities of other household members.

The probability of an activity being hidden varies based on the nature of the activity, the characteristics of the self and proxy, and other relevant factors. Activities such as household work are more visible and less likely to be hidden, as they are predominantly performed within the household. On the other hand, time spent on employment activities, which often take place outside the household, is more susceptible to concealment. Moreover, when the self and proxy are engaged in similar types of employment activities, information asymmetries may reduce due to joint participation and shared experiences.

The relationship between the self and proxy also influences the probability of hiding the time spent on any activity. In most cases, spouses tend to possess more comprehensive knowledge about each other's activities than do other household members. Consequently, when the proxy is a spouse, their reports on the time spent are expected to differ less from self-reports than when non-spouse proxies are involved.

PREDICTION 3: Asymmetric information, whether from strategic or unintentional factors, contributes to variations in the probability of overall disagreement across activity types and the characteristics of the self and proxy.

4 Data

The analysis in this paper utilizes the first nationally representative TUS in India, conducted in 2019.[1] The TUS provides comprehensive information on the time allocation of men and women in rural and urban areas across all states for 24 hours.

A total of 138,799 households were included in the TUS19 survey, covering a population of 447,250 individuals aged six years and above. Respondents were asked to report their activities over 24 hours, from 4 a.m. on the day before the survey until 4 a.m. on the day of the survey. This period was divided into 48 time slots of 30 minutes each. For each time slot, respondents could report up to three activities and designate one of them as their 'major' activity based on their subjective preference.[2] The survey was conducted throughout the week and the year, ensuring uniform representation in the responses. Details on the questions used to elicit time-use information are provided in Appendix A.

Activities were classified into nine categories based on the International Classification of Activities for Time-Use Statistics (ICATUS) of 2016, which draws on the International Labour Organization's (ILO) 2013 resolution. These include employment and related activities, production of goods for personal use, unpaid domestic services, unpaid caregiving services, unpaid volunteer work, learning, socializing, cultural participation, and self-care.

The survey also collected information on individuals' employment status, focusing on their usual principal activity during the reference period of one year. Usual principal activity is defined as the activity an individual is engaged in for the majority of the time in the previous year. Additionally, the survey gathered data on individual characteristics such as gender, education, age, occupation, and relationship to the head of the household, as well as household demographics and socioeconomic factors.

Our analysis focuses on the working-age population (15–64 years). It estimates their time allocation for four activities: employment and related activities, production of goods for personal use, unpaid domestic services, and unpaid caregiving services. These activities are particularly relevant as they are associated with the economic and non-economic dimensions of work, which is crucial for understanding the invisible work performed by women within households and its impact on labour force participation.

During the survey, individuals were intended to self-report their time-use information. So, multiple people within the household were interviewed. However, in cases where individuals were not present during the interview, other household members acted as proxy respondents and reported on their behalf. We examine the influence of the respondent's identity (self or proxy) and gender on the average time reported for each activity.

Although the survey indicates whether the time-use information was reported by the individuals themselves (self) or by proxy respondents within the household, it does not explicitly identify the proxy respondent's identity. To determine the sex identity of the proxy respondents and explore potential variations in reported time use, we employ specific deduction rules. In households with only one proxy respondent reporting on behalf of all members, we can deduce the proxy's identity.[3] For instance, in the

[1] The National Sample Survey Organization conducted a pilot TUS between July 1998 and June 1999 for six states (Gujarat, Haryana, Madhya Pradesh, Meghalaya, Orissa, and Tamil Nadu).

[2] Of all the activities performed, 65 per cent of the activities are reported as major, which is performing only one activity in a 30-minute time slot. We consider only major activity throughout our analysis.

[3] In such instances, there would be only one respondent within the household (A) reporting on time use for all members of the household, including themselves.

case of a household with three or more members, if one member reports for themselves and all other members are proxy-reported, then we know the identity of the proxy respondent.

Similarly, if multiple proxy respondents in a household share the same sex, their sex identity can be inferred.[4] For instance, in the case of a household with three or more members, if two females reported time use for themselves and also for other members, then we assign the sex of the proxy respondent as a female.

However, in cases where multiple proxy respondents do not have the same sex, it is impossible to identify the sex identity of the proxy. For instance, in the case of a household with three or more members, if one male and one female reported for themselves and other members of the household were reported by a proxy, we cannot identify the sex of the proxy respondent. For such cases, we classify the sex identity of the proxy respondent as unknown. In the TUS19 survey, approximately 64 per cent of individuals provided self-reports (of which 55 per cent are female and 45 per cent are male). In comparison, for 28 per cent of individuals the sex identity of the proxy could be identified (17 per cent reported by female proxy and 11 per cent by male proxy). In 8 per cent of cases the sex identity of the proxy informant could not be determined.

5 Estimation strategy

To examine the variations in reported time use due to differences in the identity of the reporter (self or proxy), we employ regression analysis to estimate the time spent in each of the four main activities separately. The first regression aims to determine the extent of divergence between self-reported and proxy-reported time use.

The regression model is specified as follows:

$$A_{idm} = \alpha + \theta Proxy_{idm} + \beta' X_{idm} + \gamma_d + \delta_m + \varepsilon_{idm} \tag{1}$$

where A_{idm} represents the dependent variable, namely, the reported time spent on a particular activity by individual i residing in district d and surveyed in month m. The key variable of interest is the respondent's identity, denoted by $Proxy_{idm}$. It takes value 1 if the informant is a proxy and 0 if it is a self-report. The coefficient θ captures the degree of over- or under-reporting of time spent on the activity by the proxy informant compared to self-reports.

The vector X_{idm} comprises individual and household characteristics, including age, age squared, highest level of education attained by the individual whose time use is being reported, employment status, household structure (number of adult men and women aged 15–59 years, older men and women over 65 years, and number of boys and girls under five years), and location (rural or urban). To account for variations in time use across different economic classes, we incorporate the household's quintile based on per-capita consumption expenditure. Additionally, since household production technology can affect the time allocated to household activities, we control for the type of technology employed for washing, sweeping, lighting, and cooking, as suggested in previous studies (Bardasi and Wodon 2010; de V. Cavalcanti and Tavares 2008).

To address potential variations in time use influenced by sociocultural norms and practices, we include the religion and caste of the individual. Moreover, we introduce district fixed effects to capture heterogeneity across districts due to agro-climatic conditions or other contextual factors (γ_d). Given the

[4] In such instances, two respondents within the household of the same sex (say, A and B) report on their own time use and the time use of other respondents in the household. But since both A and B have the same sex, we know the sex of the proxy as both proxy respondents have the same sex.

potential influence of seasonality on time-use patterns, we also incorporate month fixed effects (δ_m). The error term ε_{idm} represents the random component distributed across households.

We estimate this equation separately for men and women and for each of the four activities. This allows us to ascertain the differences in proxy reporting when the informant reports about men or women, compared to how men and women report about themselves[5].

The reporting of time-use information can vary due to information asymmetry regarding activity-specific time allocation by other household members, particularly when proxies are involved. Both men and women may conceal certain activities from each other. Moreover, the gender of the proxy informant may play a crucial role due to gendered disparities in information sharing and perceptions regarding gender-specific roles. Men may under-report or omit the time women spend on employment activities, household chores, or caregiving responsibilities, aligning with the social desirability bias prevalent in societies that emphasize men as providers and women as primarily responsible for household and care work (Jayachandran 2015; Press and Townsley 1998). Concurrently, men and women may perceive their own time spent within the household differently, leading to reporting biases arising from divergent perspectives. Men may acknowledge and report their involvement in household chores and caregiving, while women may perceive men's contribution as negligible and report it differently.

To assess the impact of the proxy informant's gender identity on time-use reporting, we estimate the following regression model:

$$A_{idm} = \alpha + \varphi ProxySex_{idm} + \beta' X_{idm} + \gamma_d + \delta_m + \varepsilon_{idm} \tag{2}$$

where A_{idm} denotes the dependent variable, representing the time spent in a specific activity by individual i. $ProxySex_{idm}$ is a categorical variable indicating the sex of the respondent, categorized as self, female proxy, male proxy, or unidentified proxy. As we estimate the equations separately for men and women, the gender of the self-report corresponds to the gender for which the equation is estimated. In 8 per cent of the households the data does not allow us to identify the gender identity of the proxy, as explained in Section 4. The reference category for $ProxySex_{idm}$ is self-reporting, thus the coefficient φ can be interpreted as the divergence in minutes of reported time spent on a particular activity by female proxies, male proxies, or unidentified proxies compared to self-reports. The remaining control variables are similar to those specified in Equation 1.

5.1 Matching methods

Estimating Equations 1 and 2 encounters the issue of potential endogeneity in the reported time by either self- or proxy respondents. Respondent selection is non-random, and self-respondents are more likely to be those who are available at home at the time of the survey. We document significant differences in observable characteristics of self- and proxy respondents, including gender, marital status, education, and caste. These differences may be correlated with the time use reported and hence simple differences between self- and proxy reports are not comparable.

Consequently, ordinary least squares (OLS) estimates of β would be inconsistent and biased in this context. To account for these observed and unobserved characteristics, we employ PSM and IPW. These methods allow us to estimate the average differences in outcomes (time use) between household members who self-report and those reported on by a proxy, conditional on observable covariates such as demographic characteristics—age, education, marital status—and household factors such as presence of

[5] We could have chosen to estimate the equations for the various activities simultaneously using seemingly unrelated regression (SUR) models. This would have increased the efficiency of our estimates over OLS. But since we intend to use matching methods to address the bias of non-random selection of self- and proxy respondents we use the OLS models with which matching methods can be easily applied.

adult and older men and women, children (below five years), place of residence, quintile-based monthly per-capita expenditure (MPCE), technology usage for household chores, religion, and caste. Additionally, we compare the selection based on observables with the selection based on unobservables using the Oster bound method (Oster 2019) to enhance the robustness of our analysis further.

In this sense, we create a quasi-experimental approach using secondary data due to the lack of an 'experimental setup', which is an ideal approach to address the endogeneity concern. In the literature on measurement error, an experimental approach has been utilized by Dervisevic and Goldstein (2023) to examine the influence of proxy reporting on a couple's reporting of work on each other's plots. Another strategy involves randomly assigning households to have either self-reporting or proxy-reporting of time use (Bardasi et al. 2011). However, these strategies have primarily been conducted using a smaller sample and non-nationally representative surveys. Our approach of using a nationally representative survey potentially helps provide our results with more external validity.

Propensity score matching

PSM addresses potential selection bias in our analysis. The propensity score represents the conditional probability of receiving treatment (in our case, being a proxy respondent) given the observed covariates. In other words, conditional on observable characteristics, individuals who self-report and those who are proxied do not systematically differ along unobservable dimensions. The key assumption underlying PSM is conditional independence or unconfoundedness (Hirano et al. 2003). An advantage of PSM is its robustness to model mis-specification.

We specify the propensity score as follows:

$$Proxy_{idm} = \mathrm{I}(f(X_{idm} + \delta_m) + \varepsilon_{idm} > 0) \tag{3}$$

where $\mathrm{I}(.)$ denotes the indicator variable that takes the value of 1 if its argument is true and 0 otherwise, $f(X_{idm} + \delta_m)$ represents a flexible function of all the controls, and ε_{idm} represents the unobserved determinants of proxy reporting.

We estimate the propensity scores using logit models. It is important to note that no universally best method for estimating propensity scores exists. Therefore, we present our analysis using three commonly used matching techniques: nearest-neighbour matching, k-nearest-neighbour matching, and calliper matching. In the nearest-neighbour matching approach, we compare the time use reported by proxies with those reported by self-reporting individuals with the most similar propensity scores. For the k-nearest-neighbour estimates, we consider three different values of k: $k = 1$, $k = 2$, and $k = 5$. The quality of matching using these methods is presented as the common support region for each individual in treated (proxy) and untreated (self) units (Figure A1).

Inverse propensity score weighting estimator

IPW is an alternative estimator to PSM. In this approach, treatment effects are calculated by weighting observations using the inverse of non-parametric estimates of the propensity scores. Specifically, individuals reported by proxy receive a weight of $w_i = 1/\hat{P}i$, while self-reported individuals receive a weight of $w_i = 1/(1-\hat{P}i)$, where $\hat{P}i$ denotes the estimated propensity score. The intuition behind IPW is to assign higher weights to the rare observations in the treatment group (proxied individuals) and lower weights to the more common self-reported individuals as we have more information on them.

5.2 Selection on observables and unobservables

Even after using the matching techniques, one might still be concerned that the results are an artefact of selection or omitted variable bias. In order to test the robustness of our OLS and matching results

to these results, we use a technique developed by Oster (2019). The intuition behind the technique is that selection on observables is informative about the selection on unobservables. In Equation 1 we are interested in the coefficient on the proxy variable $Proxy_{idm}$. The estimation equation has observed characteristics and ε_{idm} is the unobserved component. We would like to estimate the bias on θ of ε_{idm}. This bias can be estimated by assuming the following:

$$\frac{Cov(Proxy_{idm}, \varepsilon_{idm})}{V(X_{idm})} = \frac{\delta Cov(Proxy_{idm}, \gamma X_{idm})}{V(\gamma X_{idm})} \tag{4}$$

The assumption is that the relationship between $Proxy_{idm}$ and unobservables is proportional to the relation between $Proxy_{idm}$ and observables. Oster (2019) extends this idea and uses the change in the treatment coefficients when controls are included in the model as compared to the model with no controls to estimate the extent to which inclusion of observables reduces bias and the extent to which additional selection on unobservables would have to exist to make the treatment effect zero. For a specified R^2 we can determine the δ necessary to make the impact of treatment null. R^2 is the degree of variance a researcher would expect a model that includes both observables and unobservables to explain. The purpose of assessing unobservables using Oster bounds is to determine how significant an unobservable's influence would be to fully nullify the impact of informant identity on time use on different activities. This relationship between unobservable and observable selection depends on δ and the maximum amount of variation that can be explained by the model R_{max}. R_{max} is the maximum R-squared under the model. We select two values of R_{max}, and δ calculates an estimate of the proportional degree of selection, delta, to match a given treatment effect, beta, of informant identity.

6 Descriptive statistics

First, we present a descriptive analysis of TUS data to understand the context and distribution of time use. Time spent in the four major activities for individuals aged 15–64 is summarized in Table 1. We exclude those outside this age range as they are not in the working-age group.

Table 1: Summary statistics for individuals (15–64 years) and average time spent in four major activities

	Sample statistics (%)	Employment activity (in minutes)	Production for self-consumption (in minutes)	Unpaid domestic work (in minutes)	Unpaid care work (in minutes)
Informant identity					
Self	64	182	34	184	32
Proxy	36	250	23	119	22
Gender					
Female	49.9	75	27	293	45
Male	50.1	337	33	29	12
Marital status					
Currently married	71.7	219	32.6	188	47
Widowed/separated	5.3	211	31	210	15
Never married	22.8	254	12	84	2
Educational status					
Illiterate and below primary	27.2	192	45	201	29
Primary and upper primary/middle	27.7	225	33	168	30
Secondary and higher secondary	28.9	185	21	132	26
Diploma, graduation, and above	16.1	239	11	120	30
Usual principal activity					
Self-employed	24.4	322	65	81	16
Salaried worker	13.8	463	6	57	16
Casual worker	14.1	399	24	72	15
Attending domestic work	31.9	13	26	348	58
Unemployed	2	49	17	76	14
Other	13.8	15	10	67	9
Place of residence					
Rural	60.1	194	41	167	29
Urban	39.8	233	6	148	27
Expenditure quintile					
1	17.6	201	40	179	26
2	18.6	204	37	168	29
3	19.7	204	33	160	29
4	21.4	209	26	154	29
5	22.7	212	15	144	30
Technology usage					
Mechanical washing	13.1	206	13	145	30
Manual washing	86.8	206	32	163	28
Fuel usage					
Clean fuel for cooking	67.7	213	19	156	28
Non-clean fuel for cooking	32.2	192	51	170	30
Caste group					
General	29.1	202	23	162	27
ST	13.7	204	56	156	27
SC	17.6	214	28	163	30
OBC	39.4	205	30	160	29
Religious groups					
Hinduism	78	207	31	160	27
Islam	12.3	198	21	171	36
Christian	5.6	195	34	148	30
Others	4.1	209	28	161	26
Observations	340,366	340,366	340,366	340,366	340,366

Note: the average time use reported for different activities is unconditional on participation and weighted at the household level. The principal activity in *other* includes those attending educational institutions, rentiers, pensioners, remittance recipients, disabled, begging, prostitution, etc.

Source: authors' compilation based on TUS19.

The identity of the respondent leads to substantial differences in the reported time spent. The reported time spent by individuals who self-report on employment activities is significantly lower than that time spent by individuals who are reported by proxy respondents. The pattern is the reverse for the time spent on production for self-consumption and domestic and care work.

There are substantive differences in time use by gender, as expected in a highly patriarchal society like India. On average, women spent 78 per cent less time in employment activities than men (75 vs 337

minutes). But women spend more than ten times longer in unpaid domestic work (293 vs 29 minutes) and almost four times longer in unpaid care work than men (45 vs 12 minutes). Also, a majority of men report zero minutes spent on domestic work (90 per cent) and unpaid care work (55 per cent). The average time spent in producing self-consumption activities is similar for both men and women.

Time spent varies as expected along marital status, with married individuals involved in more household and care work, while never-married individuals do more paid work. The majority of the sample is currently married (72 per cent). Time spent by married and widowed individuals is similar in employment and production of self-consumption activities. Currently, married individuals spend 10 per cent less time on unpaid domestic work and two times more time on care activities than widowed or separated individuals. Never-married individuals spend 16 per cent more time in employment activities but 63 per cent less time in the production of self-consumption, 55 less time in domestic work, and 96 per cent less time in care work than currently married individuals. This might be partly because they are younger, so they do less production for self-consumption and might live with parents who take care of household responsibilities.

Time spent on production for self-consumption and domestic work decreases with education. Individuals with below primary education spend 4 times longer on the production of self-consumption and 1.7 times longer on unpaid domestic work than individuals with a diploma or higher education. Unpaid care work is similar across all education levels.

Individuals who are employed for more than six months or more in the year (self-employed, salaried, casual workers) spend far more time on employment activities in the previous day but spend far less time in unpaid domestic work or care work as compared to individuals who primarily are homemakers.[6] Among those classified as employed, salaried individuals spend more time on employment activities than casual workers (16 per cent more) and self-employed individuals (44 per cent more). Self-employed individuals spend the most time in production for self-consumption. They spend almost ten times longer than salaried individuals and 2.7 times longer than casual workers on production for self-consumption. This is expected as most self-employed are in agriculture and grow food for their own use.

Those who live in urban areas, on average, spend more time in employment activities (20 per cent more) and less in self-consumption (85 per cent less) and domestic work (11 per cent less). Time spent on employment activities and unpaid care work does not vary substantially by expenditure levels. But time spent on production for self-consumption and domestic work reduces as one gets richer.

Better household technology leads to a reduction in time spent on domestic work activities. Individuals living in households with a washing machine spend 12 per cent less time on domestic work. Individuals living in households using clean fuel spend 9 per cent less time on domestic activities.

There are few significant differences across social groups defined by caste and religion regarding time-use patterns across these four activities. STs spend more time in production for self-consumption, and Christians, on average, spend less time in domestic work activities than other groups. These broad descriptive findings are in line with other studies on Indian time use (Li 2023; Ratheesh and Anitha 2022; Singh and Pattanaik 2020; Srija and Vijay 2020).

The pattern of differences in reporting by self- and proxy respondents is demonstrated consistently even when self–proxy is classified by gender, region, education, class, or employment status (Table 2). This might be caused by selection bias—individuals who self-report are more likely to be at home at the time

[6] Individuals not doing employment activities for the majority of the year still spent time in the previous day on employment activities as they might be working the previous day but were not working for the majority of the time in the previous year.

of the survey and less likely to be employed full-time. To investigate this possibility, we next analyse the characteristics of individuals who self-report and those reported by a proxy.

Table 2: Heterogeneity in time use reported based on individual and household characteristics and reporting type

	Employment related			Production for consumption			Unpaid domestic work			Unpaid care work		
	Self	Proxy	Diff	Self	Proxy	Diff	Self	Proxy	Diff	Self	Proxy	Diff
All individuals (15–64)	181	247	66***	33	23	–10***	183	117	–66***	33	21	–12***
Men	316	358	42***	38	23	–16***	35	21	–13***	14	11	–3***
Female	71	85	14***	29	23	–6***	304	256	–48***	49	37	–13***
Rural	173	224	51***	49	36	–13***	184	127	–58***	33	23	–11***
Urban	193	276	83***	7	5	–2***	181	105	–76***	33	20	–14***
Highest education												
(a) Illiterate and below primary	173	234	61***	49	39	–9***	214	163	–52***	30	25	–6***
(b) Primary and upper primary	193	274	81***	38	28	–10***	192	124	–69***	35	22	–13***
(c) Secondary and above	179	238	60***	19	12	–7***	155	93	–62***	34	20	–15***
Expenditure quintiles												
1st quintile	175	222	48***	46	36	–10***	180	129	–51***	44	30	–14***
2nd quintile	176	237	61***	42	29	–12***	186	124	–62***	38	25	–13***
3rd quintile	180	242	61***	36	26	–10***	185	119	–66***	34	21	–13***
4th quintile	182	254	72***	29	18	–11***	185	115	–71***	30	19	–11***
5th quintile	189	268	78***	17	10	–8***	180	106	–74***	25	16	–9***
Activity status												
(a) Self-employed	296	370	73***	70	53	–17***	94	57	–37***	20	14	–6***
(b) Salaried worker	430	486	56***	6	4	–2***	75	42	–33***	19	15	–4***
(c) Unemployed	45	52	7**	21	14	–8***	92	64	–28***	16	11	–5***
(d) Domestic work	12	16	4***	26	23	–3***	351	335	–16***	61	51	–10***
(e) Casual worker	377	433	56***	27	17	–8***	86	50	–36***	16	14	–3***
(f) Other	13	14	1	12	6	–5***	84	45	–40***	11	7	–5***

Note: 'Diff' indicates the average time reported by the proxy for an activity subtracted from the average time reported by the self for the same activity. The average time use reported for different activities is unconditional on participation. The principal activity in *other* includes those attending educational institutions, rentiers, pensioners, remittance recipients, disabled, begging, prostitution, etc. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

Source: authors' compilation based TUS19.

Individuals who self-report their time use and those reported by someone else in the household substantially differ across a range of characteristics (Table 3). A majority of individuals (64 per cent) reported their time use themselves (self) as opposed to being reported by someone else in the household (proxy). Individuals reporting on themselves are more likely to be female. Women constitute 55 per cent of those reporting on themselves, whereas only 41 per cent of proxies are women. Self-reports are more than two years older than proxy reports. A higher proportion of self-respondents are currently married, less educated, more likely to be self-employed or homemakers, live in rural areas, are poorer, and are less likely to use household technology.

Table 3: Descriptive statistics by reporting type

	Self	Proxy	Mean difference (2) – (1)
Female	55.13	40.72	–14.41***
Male	44.86	59.27	–14.41***
Age (in years)	36.86	34.23	–2.56***
Currently married	75.20	67.10	–8.10***
Educational status			
Illiterate and below primary	29.62	22.92	–6.7***
Primary and upper primary/middle	28.41	26.57	–1.84***
Secondary and higher secondary	29.62	22.92	–6.7***
Diploma, graduation, and above	18.41	14.82	–3.28***
Majority activity status in the last year			
(a) Self-employed	24.44	22.68	–1.76**
(b) Salaried worker	10.42	17.14	6.72***
(c) Casual worker	15.03	16.91	1.88***
(d) Unemployed	1.73	1.98	0.25***
(e) Unpaid domestic activity	36.72	24.46	–12.26***
(f) Other	11.63	16.78	5.15***
Rural	70.88	64.97	–5.91***
Quintiles based on MPCE			
1st quintile	17.25	15.94	–1.31***
2nd quintile	18.38	17.76	–1.81***
3rd quintile	19.61	19.49	–0.12
4th quintile	21.48	22.35	–0.8***
5th quintile	23.21	24.42	1.21***
Household technology usage			
(a) Washing (mechanical)	10.16	13.34	3.18***
(b) Sweeping (mechanical)	4.03	5.42	1.39***
(c) Lighting (electricity, gas)	95.54	96.58	1.04***
(d) Cooking (LPG, natural/bio gas, electricity)	62.86	68.25	5.39***
Caste			
General	26.58	33.66	7.07***
ST	15.25	11.11	–4.09***
SC	17.55	17.95	0.04***
OBC	40.60	37.22	–3.33***
Religion			
Hinduism	78.41	77.33	–1.08***
Islam	11.39	13.89	2.49***
Christianity	6.05	4.72	–1.32***
Other	4.01	4.04	–0.008
Number of individuals	217,828	122,538	

Note: the table reports percentages (unless mentioned otherwise) of self- and proxy reporting for individuals with different characteristics.

Source: authors' compilation based TUS19.

7 Results

Next, we investigate whether the person who is reporting on the time use of an individual affects the reported time use, using a regression and matching framework. We study this separately for females and males to understand how reporting persons and the identity of the person being reported on influence time use.

7.1 Proxy vs self-reporting

The average treatment effect estimates obtained from various matching techniques reveal significant differences between self-reported time use and proxy-reported time use across the major activities (Table 4). Even the simple OLS results are qualitatively similar to these results (see Table A1). Specifically, proxies tend to report more time spent on employment activities for both men and women while reporting less time spent on production for self-consumption, unpaid domestic work, and unpaid care work.

Table 4: PSM and IPW estimates of time use reported (15–64 years)

	Employment activity		Production for self-consumption		Unpaid domestic work		Unpaid care work	
	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
Closet match								
Proxy	16.18***	43.31***	–2.83***	–9.42***	–11.52***	–9.83***	–6.81***	–2.13***
	(1.03)	(1.37)	(0.53)	(0.62)	(0.98)	(0.40)	(0.53)	(0.23)
Difference (%)	21.30	12.38	9.31	21.42	3.62	27.58	13.56	15.27
IPW								
Proxy	16.72***	43.79***	–2.50***	–9.71***	–11.96***	–9.86***	–7.26***	–1.86***
	(0.74)	(1.10)	(0.44)	(0.53)	(0.79)	(0.34)	(0.41)	(0.19)
Difference (%)	21.42	12.52	8.23	22	3.75	27.67	14.46	13.34
Augmented IPW								
Proxy	16.75***	43.80***	–2.50***	–9.71***	–12.01***	–9.86***	–7.27***	–1.87***
	(0.74)	(1.10)	(0.44)	(0.53)	(0.79)	(0.34)	(0.41)	(0.19)
Average time reported by self (in min)	75.93	349.69	30.37	43.96	318.09	35.63	50.19	13.94
Observations	153,608	149,504	153,608	149,504	153,608	149,504	153,608	149,504
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	153,608	149,504	153,608	149,504	154,586	149,501	153,608	149,504

Note: the dependent variable is reported time spent on each activity in minutes. The average time spent is calculated over all individuals who report for themselves, unconditional on their participation in that activity. Regression controls for individual characteristics that include age, age square, highest education completed, number of adult men and women (15–59 years), older men and women (>65 years), number of boy and girl children (<5 years), area (rural/urban), quintile based on MPCE, technology usage in washing and sweeping, sources of light and cooking, religion, and caste. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Source: authors' compilation based TUS19.

The largest absolute differences between self-reported and proxy-reported time use are observed in employment activities. This outcome can be attributed to the high time allocation in employment activities and the likelihood of these activities being performed outside the household, potentially introducing information asymmetry between self and proxy. On average, proxies report that men and women spend an additional 17 and 44 minutes, respectively, in employment activities compared to self-reports.

Furthermore, when examining the percentage differences in time reports between self and proxy across activities, we observe variations in the patterns. The percentage differences are highest for male time spent on unpaid domestic work, followed by female time spent on employment activities. On average, male time spent on unpaid domestic work is approximately 28 per cent higher than what is reported by proxies. Interestingly, self- and proxy reports align most closely for female time spent on unpaid domestic work, differing by only 4 per cent. Proxies tend to underestimate the time devoted to unpaid care work for both females and males by a similar extent, around 14 per cent. Proxies tend to overestimate the time spent on employment activities more for women (24 per cent) than for men (12 per cent).

The magnitude of these differences is stable across matching methods. PSM, IPW, and augmented IPW show almost the same magnitude of differences between self and proxy (Table 4). The results are

robust to various PSM methods with different parameters: nearest-neighbour $k = 1$, $k = 2$, and calliper matching.

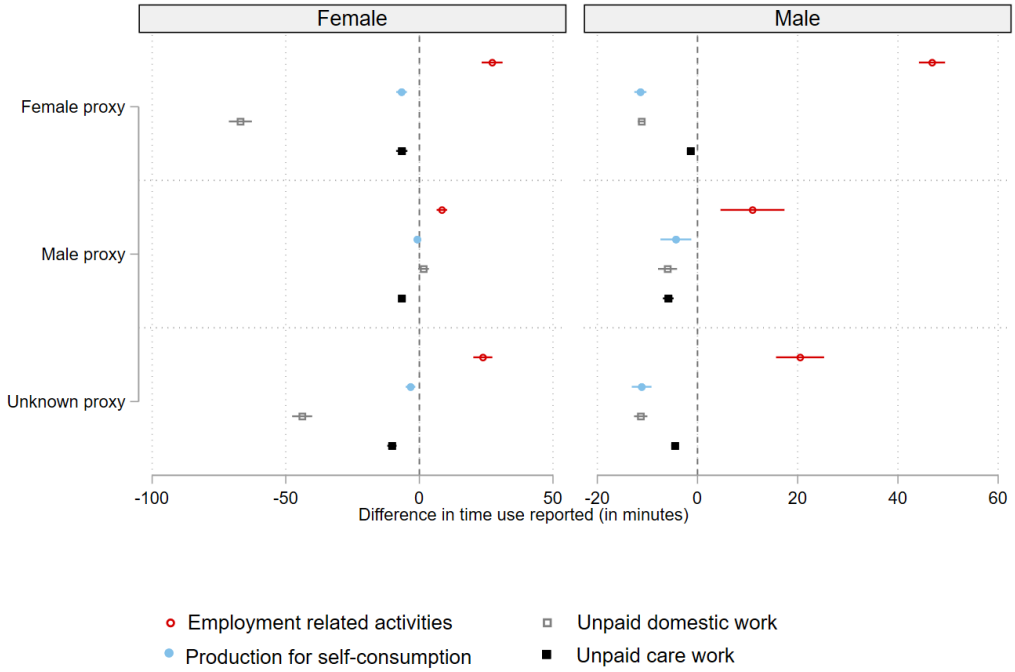
Consequently, these findings support a robust causal inference that the respondent's identity, whether self or proxy, significantly influences the reported time use and workforce participation, even after accounting for observable dimensions through matching techniques. These results underscore the importance of considering the source of information when examining time allocation patterns.

7.2 Sex of the proxy

In this section we examine how the differences between self-reports and proxy reports on time use vary depending on the sex of the proxy. We estimate Equation 2 to investigate these differences.

The findings indicate that, except unpaid care work, female proxies exhibit larger disparities in reporting compared to self-reports compared to male proxies (Figure 1). Female proxies overestimate the time spent on employment activities by 26 minutes (34 per cent) for females and 48 minutes (13 per cent) for males. In contrast, male proxies exhibit smaller differences, overestimating employment time by only 9 minutes (11 per cent) for females and 12 minutes (3 per cent) for males.

Figure 1: Coefficient plot (using IPW estimates) for reported time use (15–64 years) by sex of the proxy



Note: the dependent variable is the reported time spent on each activity in minutes. Regression controls for individual characteristics that include age, age squared, highest education completed, number of adult men and women (15–59 years), older men and women (>65 years), number of boy and girl children (<5 years), area (rural/urban), quintile based on MPCE, technology usage in washing and sweeping, sources of light and cooking, religion, and caste.

Source: authors' compilation based on TUS19.

Examining the other major activities, we observe that male proxies closely align with female self-reports for time spent on production for self-consumption and unpaid domestic work. However, female proxies' reports significantly deviate from self-reports in these activities. Female proxies tend to underestimate time spent on production for self-consumption by 6.5 minutes (22 per cent) for females and 11.3 minutes (29 per cent) for males. Similarly, they underestimate time spent on unpaid domestic work by 66.4 minutes (21 per cent) for females and 11.5 minutes (33 per cent) for males.

Interestingly, when it comes to time spent on unpaid care work by males, female proxies are closer to self-reports than male proxies. Female proxies underestimate male time spent on unpaid care work by 1.4 minutes (9 per cent), while male proxies underestimate it by 6 minutes (41 per cent).

In approximately 8 per cent of cases, the sex of the proxy could not be identified due to data limitations (as discussed in Section 4). These cases are included in our analysis as 'unknown sex of proxy'. The OLS estimates exhibit similar patterns to the IPW estimates, providing further support for our findings (see Table A2).

Overall, these results highlight the importance of considering the sex of the proxy when analysing time-use data. Female proxies tend to introduce larger discrepancies in reporting, particularly for employment activities and certain household-related tasks. These insights contribute to our knowledge of the complexities of collecting accurate time-use data.

8 Mechanisms

The differences in reporting by self- and proxy responses might arise through various pathways. Results till now show that self- and proxy reports are systematically different, ruling out that random measurement error is the only form of error leading to the self–proxy differences. The differences vary by sex—female proxies have larger differences from self-reports than male proxies have with self-reports. This indicates that, as hypothesized, perceptions of time spent on different activities might vary by gender, so asymmetric measurement error might be a reason for the overall difference. The differences are larger in activities where perceptions of time spent are more likely to differ because they are less common and more disputed—female employment and unpaid domestic work by men. This is another indication that asymmetric measurement error plays a role.

In this section, we perform additional tests to investigate whether asymmetric information error (spouse vs non-spouse proxy, matching characteristics of proxy and person being reported on) and asymmetric measurement error (gender norms) are reasons for the self–proxy reporting differences.

8.1 Asymmetric information error

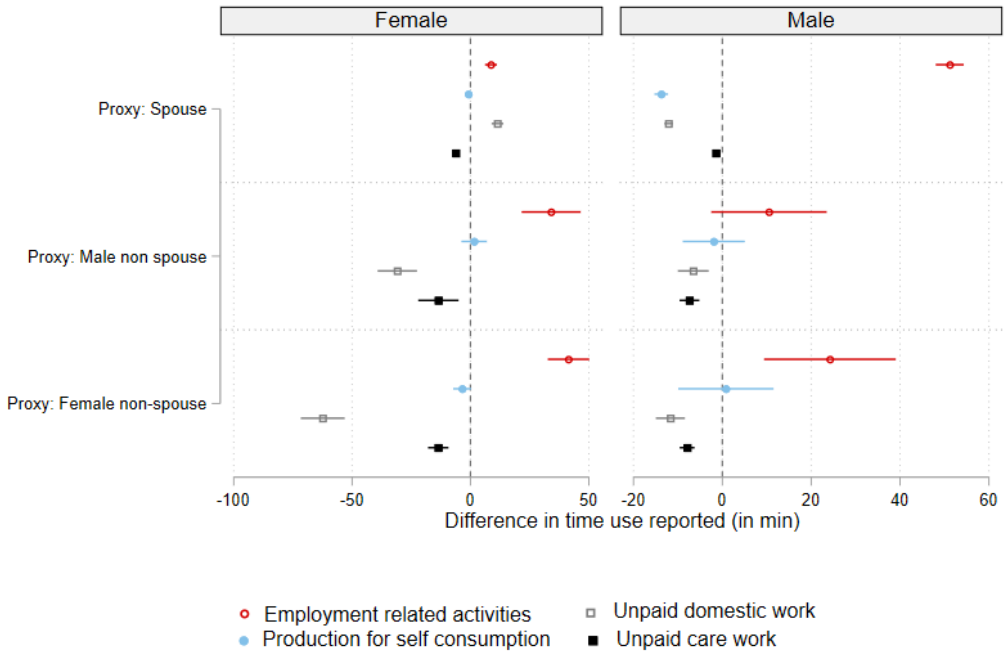
Spouse vs non-spousal response

We hypothesize that spouses are more likely to share detailed information about their day-to-day activities than other household members. Consequently, when the proxy respondent is the spouse, we expect the differences between self-reported and proxy-reported time use to be smaller than when the proxy is a non-spouse. To investigate this, Figure 2 presents the results of our analysis, which estimates the difference in self-reported and proxy-reported time use for spouse proxies and non-spouse female and male proxies.

We need to identify whether the proxy is the spouse or not of each proxied individual. However, the data does not allow us to identify the exact proxy for each individual when multiple proxies are present in the household. Hence we focus on households with a single proxy respondent. Additionally, given that we only have information on the relationship to the head of the household, we further restrict the sample to the head and the spouse of the head. The estimates then compare households where the head or their spouse report on themselves and their spouse with households where other household members report on the primary couple.

For women's time use, the differences between self-reports and spouse reports are generally smaller than between self-reports and non-spouse reports across various activities. Specifically, spouses report 8

Figure 2: Coefficient plot (using IPW estimates) for measuring asymmetric information



Note: the dependent variable and controls are the same as mentioned in Figure 1.

Source: authors' compilation based on TUS19.

minutes more time spent in employment than self-reports, whereas non-spouse proxies report between 34 and 41 minutes more. Regarding unpaid domestic work, spouses estimate women spend 11 minutes more time than they self-report, while non-spouse proxies report between 31 and 62 minutes less time than that reported by self. Female non-spouses tend to have higher deviation from self reports as compared to male non-spouses.

However, when reporting about men, wives' reported time differs more from men's own reporting than other household members. This is particularly pronounced for time reported on men's employment activities, where wives over-report by 52 minutes compared to men's self-reporting, while other household members over-report between 10 and 24 minutes.

These differences in reporting may be influenced by information asymmetry, whereby men and women have differential knowledge about employment activities. It is possible that since women are less likely to engage in employment activities outside the house, they have less accurate information about the time spent on such activities, leading to greater differences from self-reports. In contrast, men better understand employment activities and can provide more accurate estimates of time spent. We obtained similar results when investigating differences in proxy reporting by sex in Section 7.

Measures of bargaining power: age difference

In the theoretical framework we hypothesized that women with higher bargaining power might lead to better information sharing and lower information asymmetry. In the Indian TUS there are no variables to directly test the bargaining power; however, we considered intra-household bargaining power between spouses by measuring their age differences. We expect that with higher age gaps, women will have lower bargaining power and, hence, higher time-use differences.

When the age gap between the proxy and the person being reported on is smaller (less than ten years), the self–proxy reporting differences are smaller than when the age gap is more than ten years (Table 5).

Table 5: IPW estimates of self–proxy reporting differences by age differences

	Employment activity		Production for self-consumption		Unpaid domestic work		Unpaid care work	
	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
Type of respondent (base: self)								
Proxy: age difference from self less than ten years	10.68***	46.50***	–0.69	–10.22***	8.71***	–9.47***	–7.20***	–1.01***
	(1.36)	(1.70)	(0.68)	(0.75)	(1.27)	(0.53)	(0.57)	(0.28)
Proxy: age difference from self more than ten years	23.68***	35.24***	–5.17***	–9.29***	–33.44***	–9.37***	–11.11***	–3.37***
	(1.41)	(2.07)	(0.75)	(1.01)	(1.49)	(0.60)	(0.75)	(0.37)
Average time reported by self (in min)	76.21	355.43	30.04	38.98	313.65	35.68	51.25	14.89
Observations	141,741	132,106	141,741	132,106	141,741	132,106	141,741	132,106

Note: see Table 4 notes for details on dependent variables and controls. Respondents are classified into three categories: self, proxy whose age difference from the self is less than ten years, and proxy whose age difference from the self is ten years or more.

Source: authors' compilation based on TUS19.

Similar characteristics: occupation

We hypothesize that when the proxy and the person they report on have similar characteristics, it reduces asymmetric information and the difference in self- and proxy reporting. We test this by comparing proxies that are engaged in the same occupation type as the person they are responding to with those that are engaged in different kinds of activities. Table 6 shows that when there is an activity match, self–proxy reporting differences on employment and production for self-consumption are smaller than when activities are different (for both female and male proxies).

Table 6: IPW estimates of self–proxy reporting differences by the matching activity type

	Employment activity		Production for self-consumption		Unpaid domestic work		Unpaid care work	
	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
Type of respondent (base: self)								
Proxy: female and activity matches with self	9.17**	18.31***	–2.81	–4.29***	–61.05***	–10.09***	–7.18***	–1.50***
	(4.00)	(3.25)	(1.71)	(1.54)	(2.86)	(0.87)	(1.40)	(0.56)
Proxy: male and activity matches with self	7.33***	–18.80***	–1.48	0.18	–7.21***	–1.57	–20.00***	–6.55***
	(1.70)	(5.87)	(1.20)	(2.44)	(2.54)	(1.92)	(1.18)	(1.07)
Proxy: female and activity different than self	32.02***	48.01***	–10.51***	–13.01***	–60.00***	–10.88***	–3.79	–1.61***
	(3.76)	(1.61)	(1.60)	(0.69)	(5.89)	(0.54)	(3.52)	(0.27)
Proxy: male and activity different than self	20.06***	25.69***	–5.63***	–13.17***	–2.15*	–8.85***	–6.89***	–5.76***
	(1.48)	(4.40)	(0.63)	(1.99)	(1.21)	(1.28)	(0.57)	(0.80)
Average time reported by self (in min)	76.44	355.95	29.97	38.98	313.57	35.75	51.17	14.88
Observations	141,736	132,100	141,736	132,100	141,736	132,100	141,736	132,100

Note: see Table 4 notes for details on dependent variables and controls. Respondents are classified into four categories by gender and activity match with self. Activity match means that both self and proxy are in the same type of activity. Activities are classified into four types: salaried, self-employment/contributing, casual worker, or other.

Source: authors' compilation based on TUS19.

8.2 Asymmetric measurement error

Gender norms

The differences in self–proxy reporting are partly driven by differences in gender norms held by women and men. If both hold similar norms, then we don't expect large reporting differences. In contrast, if there is contention in gender norms held by women and men, then it would be reflected in the definitions and interpretations of activities as work and the associated reporting. If women and men agree that women should not work outside and view different tasks done by women as part of their household

work duties, then both would report less time spent in employment activities. If both women and men believe it is acceptable for women to work, then women's activities would be correctly classified as work by both and the self–proxy difference would be lower. If women think it is work, but men do not, then women might interpret their activities as work but men might refuse to do that, leading to differences in self–proxy reporting.

We use caste as a proxy for gender norms as the time use data lacks direct information on norms or decision-making. Gender norms vary substantially by caste. Women working outside the home is considered a low-status activity, whereas child-rearing and household work are considered high-status for women. This is especially true of upper caste women (Eswaran et al. 2013; Rao 2014; Srinivas 1956). This is also reflected in the variation in time women spend in employment activities across the caste groupings. Upper caste women spend almost half their time in employment activities as compared to ST women (Table 7).

Relative self–proxy differences in time spent on employment for women are substantially larger for upper caste women compared to other castes (50 per cent vs 25–33 per cent for other castes) (Table 7). This might be because upper caste women and men disagree on gender norms related to working and hence reporting differences arise. On the other hand, for men there is no systematic pattern of differences between caste groups.[7]

[7] Muslim women spend about half their time in employment activities as compared to women from other religions, but self–proxy reporting differences are not substantive across religious groups (results available on request).

Table 7: IPW estimates of time use reported (15–64 years) by caste categories

	Employment activity (in min)		Production for self-consumption (in min)		Unpaid domestic work (in min)		Unpaid care work (in min)	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)
Caste category: general								
Proxy	26.39***	47.96***	–2.17***	–6.17***	–23.51***	–10.90***	–7.38***	–2.23***
	(1.55)	(2.08)	(0.59)	(0.71)	(1.43)	(0.56)	(0.66)	(0.30)
Difference (%)	50	15.54	9.98	19.16	7.51	30.79	16.13	19.02
Average reported by self (in min)	52.77	308.47	21.73	32.19	313.04	35.39	45.75	11.72
Observations	49,672	50,834	49,672	50,834	49,672	50,834	49,672	50,834
Caste category: ST								
Proxy	28.71***	41.01***	–6.13***	–9.34***	–23.33***	–8.91***	–12.31***	–3.41***
	(2.88)	(3.13)	(1.57)	(1.79)	(2.19)	(0.91)	(1.08)	(0.51)
Difference (%)	30.15	14.48	10.76	13.99	8.16	24.69	28.62	25
Average reported by self (in min)	95.21	283.19	56.97	66.76	285.61	36.08	43	13.64
Observations	23,930	23,771	23,930	23,771	23,930	23,771	23,930	23,771
Caste category: SC								
Proxy	25.19***	46.56***	–2.47***	–10.12***	–18.51***	–9.25***	–6.61***	–0.11
	(2.35)	(2.64)	(0.87)	(0.99)	(1.91)	(0.72)	(0.88)	(0.41)
Difference (%)	32.88	14.45	9.31	27.45	6.08	27.25	13.44	0.85
Average reported by self (in min)	76.60	322.12	26.51	36.86	304.07	33.94	49.18	12.92
Observations	30,600	30,855	30,600	30,855	30,600	30,855	30,600	30,855
Caste category: OBC								
Proxy	17.79***	43.07***	–1.12*	–8.92***	–16.83***	–9.13***	–6.85***	–1.37***
	(1.52)	(1.79)	(0.60)	(0.71)	(1.29)	(0.47)	(0.59)	(0.27)
Difference (%)	24.62	13.85	4.16	23.22	5.67	28.71	14.56	10.62
Average reported by self (in min)	72.25	310.88	26.88	38.40	296.54	31.79	47.02	12.90
Observations	68,745	68,442	68,745	68,442	68,745	68,442	68,745	68,442
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: for details on controls, refer to Table 4. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: authors' compilation based on TUS19.

9 Heterogeneity test

As noted by Srivastava (2020), gender norms affect an individual's autonomy and time use inside the household in complex ways, particularly in South Asia, and are frequently mediated by social institutions such as economic status. Region-specific heterogeneity may also influence gender norms in India. Therefore, in this section we investigate heterogeneity in the differences in self–proxy reporting of time use along various dimensions.

9.1 Rural/urban

Table 8 presents the results for rural and urban samples separately. The patterns in each region are similar to the overall results, with self- and proxy reports differing significantly in the same direction as the overall results. For employment activities, the relative differences between self and proxy are larger in rural areas than in urban areas. In contrast, for household work (domestic and care) proxies in urban areas differ from self-reporting more than proxies in rural areas. The nature of employment activities in rural and urban areas might drive this. In rural areas, activities are more likely to be multiple and fragmented, whereas in urban areas they are likely to be more defined.

Even when the analysis is done by sex of the proxy, we find similar patterns in each region across gender as those found in overall results (Table A3). Female proxies have larger differences from self-

Table 8: IPW estimates of time use reported (15–64 years) by rural and urban status

	Employment activity (in min)		Production for self-consumption (in min)		Unpaid domestic work (in min)		Unpaid care work (in min)	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)
Rural								
Proxy	17.37***	47.20***	–3.137***	–15.06***	–8.972***	–8.770***	–6.492***	–1.643***
	(17.13)	(32.25)	(–4.64)	(–18.22)	(–8.92)	(–19.22)	(–12.41)	(–6.53)
Difference (%)	22.68	14.41	7.88	25.85	2.79	23.53	12.98	11.46
Average time reported by self (in min)	76.57	327.52	39.72	58.24	321.11	37.27	49.99	14.30
Observations	94,958	90,210	94,958	90,210	94,958	90,210	94,958	90,210
Urban								
Proxy	13.74***	37.75***	–1.47***	–0.99**	–16.02***	–11.15***	–8.66***	–2.24***
	(13.60)	(22.63)	(–4.82)	(–2.48)	(–12.57)	(–22.44)	(–13.01)	(–7.42)
Difference (%)	18.48	9.25	20.44	15.34	5.15	35.58	17.08	17.20
Average time reported by self (in min)	74.34	407.91	7.19	6.45	310.62	31.33	50.68	13.02
Observations	58,650	59,294	58,650	59,294	58,650	59,294	58,650	59,294
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: for details on dependent variable and controls, refer to Table 4. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Source: authors' compilation based on TUS19.

reports than male proxies have from self-reports in both regions across all activities except unpaid care work.

9.2 Across welfare levels

Tables A4 and A5 present results for self–proxy differences by consumption quintiles separately in rural and urban areas. As households get richer the differences between self- and proxy reports are larger for female employment activity, but there is no systematic pattern for men's employment activities. In none of the other activities are there clear systematic patterns across quintiles.

9.3 Region

Table A6 presents results for differences in reporting by geographical regions. India is a large and diverse country, with regions differing substantively in economy, culture, gender norms, and development, so it's important to understand heterogeneity in reporting by region. We divide the country into six regions. Central and eastern regions are among the poorest, with low levels of women's empowerment. In contrast, south and western regions are more economically developed and have relatively more women's empowerment in decision-making and mobility (Gupta and Yesudian 2006; Kishor and Gupta 2004). Women's empowerment can be partially observed in women's time spent in employment. In eastern and central regions, time spent by women in employment activities and production of self-consumption is far lower than that spent by women in southern and western regions.

Proxy reporting of employment activities for women differs from self-reporting in both absolute and relative terms, mostly in western and southern regions (44–54 per cent compared to 7–35 per cent in other regions). Reporting on domestic and care work is closest to self-reports in central and eastern regions (2–7 per cent difference vs 8–28 per cent differences in other regions).

10 Robustness check

10.1 Oster bounds

Our results suggest informant identity and sex of informant identity derives from the differences in the time use reported. However, to establish the robustness of the results we consider using an approach suggested by Oster (2019) to factor in unobserved heterogeneity.

In Table 9 we present the results for Oster bounds, which compares controlled and uncontrolled regression with fixed effects and assumes certain relations between observables and unobservables. Oster (2019) shows that if the coefficient is stable after the inclusion of controls, then omitted variable bias must be limited. With observed variation (R_{max}) set at 0.7 and 1, comparing the two sets of coefficients gives us results similar to our main finding. The different values of δ define the importance of the unobservables relative to the observables in influencing β coefficients of our regression and R_{max} represents hypothetical regression that controls for all observable and unobservable factors.

Table 9: Assessing the effect of unobservables using Oster bounds

	Employment activity (in min)		Production for self-consumption (in min)		Unpaid domestic work (in min)		unpaid care work (in min)	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)
$R_{max} = 1.3 \times R^2$								
Uncontrolled	23.37***	62.76***	–4.22***	–16.51***	–28.22***	–13.34***	–9.46***	–2.69***
	[0.004]	[0.017]	[0.001]	[0.006]	[0.007]	[0.010]	[0.002]	[0.001]
Controlled	18.09***	42.88***	–2.58***	–8.73***	–13.45***	–9.51***	–6.67***	–1.90***
	[0.489]	[0.269]	[0.113]	[0.099]	[0.263]	[0.054]	[0.343]	[0.120]
δ for $\beta = 0$ given R_{max}	9.06	5.21	5.58	2.87	3.10	9.54	6.87	7.42
$R_{max} = 1$								
Uncontrolled	23.37***	62.76***	–4.22***	–16.51***	–28.22***	–13.34***	–9.46***	–2.69***
	[0.004]	[0.017]	[0.001]	[0.006]	[0.007]	[0.010]	[0.002]	[0.001]
Controlled	18.09***	42.88***	–2.58***	–8.73***	–13.45***	–9.51***	–6.67***	–1.90***
	[0.489]	[0.269]	[0.113]	[0.099]	[0.263]	[0.054]	[0.343]	[0.120]
δ for $\beta = 0$ given R_{max}	2.52	0.62	0.17	0.10	0.28	0.10	1.03	0.26
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	153,608	149,504	153,608	149,504	154,586	149,501	153,608	149,504

Note: R^2 in square brackets. For details on controls, refer to Table 4.

Source: authors' compilation based on TUS19.

10.2 LASSO results

The least absolute shrinkage and selection operator (LASSO) estimates model coefficients, and these estimates can be used to select which covariates should be included in a model. We present the estimates using the LASSO technique in Table A7. The results are in line with the main results, indicating that proxies tend to estimate more time spent in employment-related activities for both females and males compared to self-reports, and less time spent in production for self-consumption, unpaid domestic work, and care work.

10.3 Day of the week effect

The TUS19 collects data from an equal number of households across the week. However, the day of the survey capturing their 24 hours can affect the time use reported. For instance, data collected on Monday from certain households may differ from a household whose data was collected on Saturday. We control for the heterogeneity arising from the day of a survey by including the 'day of the week' fixed effect. The results using such specification are presented in Table A8 using PSM and IPW estimates, which yields results robust to our main findings. The proxy reports more time (21 and 12 per cent) spent on employment-related activities for women and men, respectively, and less time on all other activities.

11 Discussion and conclusion

Low-cost surveys such as direct observation are the most common method of collecting time-use data in low economic settings. However, due to the choice of respondent and heterogeneity in the individual characteristics of the informants, differences may cause non-random measurement errors. These possible biases are rarely assessed in the time-use data, an important statistic to unpack the relation between women's autonomy, gendered roles, and division of labour within the household. This paper analyses whether the informant's identity (and related mediating characteristics) matters in estimating time use in four major activities. Using a quasi-experimental setup on nationally representative data from India, we estimated the differences in time use reported when the respondents were interviewed personally or through a proxy (another household member). The impact of informant selection on time-use reports varies by the gender of those who are reporting as well as the persons being reported on.

At an aggregate level, individuals reporting for themselves, compared to a proxy informant, report more time spent in all activities except for employment-related work. There can be two plausible mechanisms at play here. First, inconsistency in the perceived notion of domestic work by another member, hence proxy reports 14 and 10 minutes lower for women and men, respectively. In other words, self-reports overstate to make them appear to be working as it 'looks better' (Bardasi et al. 2011). Second, for employment activities, a proxy member over-reports by 18 minutes and 43 minutes for women and men, respectively, which could be due to (a) lack of direct observation of employment work as it includes time spent on commuting, socialization, and meal breaks at the workplace; and (b) members of the households possibly hiding their employment work from other members.

These findings have policy c onsequences. B iases in reporting caused by questioning only one spouse may result in interventions that target the wrong individuals within families or inappropriate households (Ambler et al. 2022). These findings clearly show that national statistical agencies and other researchers should carefully think through the selection of respondents in their TUS. Also, researchers should interpret the findings, taking the identity of the respondent in the survey into account. As TUS become more common across the developing world and are used more often to determine women's role in economic and non-economic activity, measurement issues become more critical.

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Appendix A

Description of the time-use questions

Particulars of activities for each household member of age six years and above from 4:00 a.m. on the day before the date of the interview to 4:00 a.m. on the day of the interview.

Summary statistics for individuals (15–64 years) and average time spent in four major activities

1. Record in 24-hour clock format (from 4:00 a.m. before the day of the interview to 4:00 a.m. on the day of the interview)
2. Whether performed multiple activities in the time slot (yes = 1, no = 2)
3. If yes, whether simultaneous activity (yes = 1, no = 2)?
4. Description of the activity (at most three activities for each 30-minute time slot)
5. Whether a major activity or minor activity (major = 1 /minor = 2)
6. Three-digit activity code of TUS classification of activities
7. Where the activity was performed. (Within premises of the dwelling = 1, outside premises of the dwelling = 2, non-fixed location = 3)
8. Status of the activity—unpaid or paid?[8]
9. Type of enterprise?[9]

[8] Unpaid activity code: self-development/self-care/self-maintenance, etc. = 01; care for children, sick, elderly, differently abled persons in own households = 02; production of other services (except care activities as covered in code 02) for own consumption = 03; production of goods for own consumption = 04; voluntary work for production of goods in households = 05; voluntary work for production of services in households = 06; voluntary work for production of goods in market/non-market units = 07; voluntary work for production of services in market/non-market units = 08; unpaid trainee work for production of goods = 09; unpaid trainee work for production of services = 10; other unpaid work for production of goods = 11; other unpaid work for production of services = 12. Paid activity code: self-employment: for production of goods = 13; for production of services = 14. Regular wage/salary: for production of goods = 15; for production of services = 16. Casual labour: for production of goods = 17; for production of services = 18.

[9] Type of enterprise code: proprietary = 1, partnership = 2, government/local body = 3, autonomous bodies = 4, public/private limited company = 5, cooperative societies = 6, trust/other non-profit institutions = 7, employer's households (i.e., private households employing maid servant, watchman, cook, etc.) = 8, others = 9.

Table A1: OLS estimates of reported time use of working-age individuals (15–64 years)

	Employment activity		Production for self-consumption		Unpaid domestic work		Unpaid care work	
	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
Proxy	18.09***	42.88***	–2.59***	–8.73***	–13.46***	–9.51***	–6.77***	–1.90***
	(0.71)	(1.11)	(0.43)	(0.53)	(0.76)	(0.35)	(0.40)	(0.20)
Difference (%)	23.82	12.29	8.52	19.85	4.23	26.66	13.48	13.62
Average time reported by self (in min)	75.93	349.69	30.37	43.96	318.09	35.63	50.19	13.94
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	153,608	149,504	153,608	149,504	153,608	149,504	153,608	149,504
R^2	0.49	0.27	0.11	0.10	0.26	0.05	0.34	0.12
F	1,336.53	498.79	177.48	148.63	498.26	77.83	723.97	184.22

Note: dependent variable is reported time spent on each activity in minutes. The average time spent is calculated over all individuals who report for themselves, unconditionally on their participation in that activity. Regression controls for individual characteristics that include age, age squared, highest education completed, number of adult men and women (15–59 years), older men and women (>65 years), number of boy and girl children (<5 years), area (rural/urban), quintile based on MPCE, technology usage in washing and sweeping, sources of light and cooking, religion, and caste. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Source: authors' compilation based on data.

Table A2: OLS results: time use reported when sex of proxy respondents can be identified (15–64 years)

	Employment activity (in min)		Production for self-consumption (in min)		Unpaid domestic work (in min)		Unpaid care work (in min)	
	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
Type of respondent (base: self)								
Female proxy	33.11***	47.71***	–6.74***	–9.80***	–43.91***	–11.01***	–8.21***	–1.47***
	(1.47)	(1.25)	(0.88)	(0.60)	(1.58)	(0.40)	(0.87)	(0.23)
Male proxy	11.02***	25.78***	–0.83	–1.56	–0.77	–3.99***	–6.95***	–3.12***
	(0.87)	(2.54)	(0.52)	(1.21)	(0.94)	(0.81)	(0.52)	(0.46)
Unknown proxy	25.13***	39.20***	–3.43***	–8.93***	–24.06***	–9.45***	–6.45***	–2.49***
	(1.30)	(2.03)	(0.78)	(0.97)	(1.40)	(0.65)	(0.77)	(0.37)
Average time reported by self (in min)	75.93	349.69	30.37	43.96	318.09	35.63	50.19	13.94
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	152,704	148,742	152,704	148,742	152,704	148,742	152,704	148,742
R^2	0.49	0.26	0.11	0.10	0.26	0.05	0.33	0.11
F	3,434.45	1,178.34	419.49	299.33	1,241.34	187.05	1,756.24	445.10

Note: individual characteristics include age, age squared, highest education completed, number of adult men and women (15–59 years), older men and women (>65 years), and boy and girl children (<5 years), rural/urban, quintile based on MPCE, technology usage in washing and sweeping, sources of light and cooking, religion, and caste. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Source: authors' compilation based on TUS19.

Table A3: IPW estimates by sex identity of proxy for reported time use (15–64 years) for rural and urban sub-sample

	Employment activity		Production for self-consumption		Unpaid domestic work		Unpaid care work	
	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
Type of respondent (base: self): rural								
Female proxy	32.27***	53.95***	–9.82***	–17.96***	–66.74***	–9.05***	–6.54***	–1.01***
	(11.02)	(30.79)	(–6.21)	(–18.66)	(–23.49)	(–17.28)	(–4.80)	(–3.40)
Male proxy	9.49***	11.90***	–0.54	–7.38***	2.97**	–6.52***	–5.59***	–6.39***
	(7.22)	(2.77)	(–0.61)	(–3.01)	(2.33)	(–4.97)	(–8.79)	(–10.52)
Unknown proxy	27.37***	19.34***	–4.09***	–16.34***	–41.33***	–12.17***	–9.51***	–4.56***
	(10.86)	(5.95)	(–2.86)	(–10.12)	(–16.79)	(–13.27)	(–8.18)	(–8.91)
Average time reported by self (in min)	76.57	327.52	39.72	58.24	321.11	37.27	49.99	14.30
Observations	95,231	90,582	95,231	90,582	95,231	90,582	95,231	90,582
Type of respondent (base: self): urban								
Female proxy	22.11***	35.81***	–1.47**	–1.06**	–65.96***	–14.37***	–6.80***	–2.003***
	(8.47)	(17.59)	(–2.09)	(–2.37)	(–19.26)	(–27.82)	(–4.00)	(–6.07)
Male proxy	5.55***	8.65*	–1.04***	0.12	0.046	–5.42***	–8.03***	–4.81***
	(3.79)	(1.71)	(–2.61)	(0.11)	(0.03)	(–3.82)	(–9.68)	(–4.54)
Unknown proxy	16.57***	15.94***	–2.29***	–1.95***	–47.63***	–9.65***	–11.80***	–4.69***
	(6.53)	(4.30)	(–4.16)	(–2.70)	(–15.57)	(–9.42)	(–8.82)	(–8.96)
Average time reported by self (in min)	74.34	407.91	7.19	6.45	310.62	31.33	50.68	13.02
Observations	58,891	59,548	58,891	59,548	58,891	59,548	58,891	59,548
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: the dependent variable is reported time spent on each activity by the individual. For details on controls, refer to Table 4. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Source: authors' compilation based on TUS19.

Table A4: IPW estimates of time use reported (15–64 years) by consumption quintile: rural residence

	Employment activity (in min)		Production for self-consumption (in min)		Unpaid domestic work (in min)		Unpaid care work (in min)	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)
Rural sub-sample								
1st quintile								
Proxy	16.76***	47.92***	–5.58***	–14.84***	–6.44***	–12.91***	–7.15***	–2.20***
	(2.95)	(3.27)	(1.36)	(1.74)	(2.31)	(1.05)	(0.97)	(0.46)
Difference (%)	19.84	16.40	13.53	25.20	2.05	27.42	17.48	17.68
Average time reported by self (in min)	84.47	292.17	41.22	58.87	312.83	47.08	40.89	12.44
Observations	23,831	21,757	23,831	21,757	23,831	21,757	23,831	21,757
2nd quintile								
Proxy	19.90***	37.18***	–2.03	–13.03***	–13.28***	–7.13***	–5.63***	–1.43***
	(2.88)	(3.31)	(1.48)	(1.77)	(2.34)	(0.98)	(1.13)	(0.53)
Difference (%)	27.96	12.49	5.21	22.76	4.18	20.56	11.69	10.37
Average reported by self (in min)	71.16	297.65	38.90	57.24	317.11	34.67	48.12	13.78
Observations	19,289	19,089	19,289	19,089	19,289	19,089	19,289	19,089
3rd quintile								
Proxy	21.12***	39.61***	1.73	–15.44***	–17.41***	–6.66***	–6.61***	–1.27**
	(2.65)	(3.15)	(1.43)	(1.60)	(2.28)	(0.89)	(1.08)	(0.51)
Difference (%)	31.31	13.41	4.84	28.05	5.62	20.85	13.41	9.22
Average reported by self (in min)	67.44	295.18	35.69	55.05	309.62	31.93	49.29	13.76
Observations	20,702	21,078	20,702	21,078	20,702	21,078	20,702	21,078
4th quintile								
Proxy	21.21***	46.06***	–3.76***	–12.08***	–18.23***	–7.55***	–7.73***	–1.50***
	(2.56)	(3.15)	(1.35)	(1.54)	(2.24)	(0.84)	(1.04)	(0.49)
Difference (%)	31.45	15.75	10.46	24.81	6.10	24.77	16.13	11.87
Average time reported by self (in min)	67.44	292.43	35.92	48.69	298.72	30.48	47.91	12.63
Observations	20,842	21,102	20,842	21,102	20,842	21,102	20,842	21,102
5th quintile								
Proxy	20.32***	46.50***	–5.87***	–12.42***	–23.23***	–6.72***	–8.82***	–2.35***
	(2.35)	(3.21)	(1.33)	(1.49)	(2.18)	(0.84)	(1.06)	(0.51)
Difference (%)	33.37	16.06	16.79	28.15	8.09	24.08	17.53	17.31
Average time reported by self (in min)	60.88	289.36	34.95	44.11	286.96	27.90	50.31	13.57
Observations	20,820	21,073	20,820	21,073	20,820	21,073	20,820	21,073
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: for details on controls, refer to Table 4. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Source: authors' compilation based on TUS19.

Table A5: IPW estimates of time use reported (15–64 years) by consumption quintile: urban residence

	Employment activity (in min)		Production for self-consumption (in min)		Unpaid domestic work (in min)		Unpaid care work (in min)	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)
Urban sample								
1st quintile								
Proxy	10.35***	53.63***	–1.93**	–0.14	–13.57***	–16.92***	–11.25***	–0.06
	(3.88)	(4.35)	(0.77)	(0.97)	(3.05)	(1.18)	(1.25)	(0.59)
Difference (%)	11.73	15.44	20.42	1.86	4.88	40.40	30.53	0.75
Average time reported by self (in min)	88.18	347.18	9.45	7.52	277.66	41.88	36.84	7.97
Observations	13,739	14,643	13,739	14,643	13,739	14,643	13,739	14,643
2nd quintile								
Proxy	23.57***	42.39***	–0.87	–1.09	–23.54***	–9.93***	–9.64***	–2.00***
	(3.19)	(3.74)	(0.66)	(0.82)	(2.68)	(0.91)	(1.21)	(0.51)
Difference (%)	34.86	11.77	11.02	16.19	7.80	35.42	20.30	18.83
Average reported by self (in min)	67.60	359.90	7.89	6.73	301.53	28.03	47.47	10.62
Observations	14,830	15,633	14,830	15,633	14,830	15,633	14,830	15,633
3rd quintile								
Proxy	27.18***	48.33***	–3.19***	–1.89**	–22.92***	–9.55***	–6.24***	–1.27**
	(3.63)	(4.36)	(0.62)	(0.76)	(3.08)	(1.06)	(1.52)	(0.63)
Difference (%)	44.10	13.84	46.03	32.30	7.73	35.90	12.69	10.83
Average reported by self (in min)	61.62	349.14	6.93	5.85	296.20	26.60	49.16	11.72
Observations	11,564	11,976	11,564	11,976	11,564	11,976	11,564	11,976
4th quintile								
Proxy	34.92***	47.27***	–0.94**	–1.76***	–32.62***	–7.36***	–9.41***	–3.37***
	(3.34)	(3.93)	(0.46)	(0.60)	(2.75)	(0.94)	(1.30)	(0.58)
Difference (%)	56.34	13.38	19.10	41.90	11.13	32.78	18.62	25.82
Average time reported by self (in min)	61.98	353.16	4.92	4.20	292.91	22.45	50.52	13.05
Observations	13,592	13,935	13,592	13,935	13,592	13,935	13,592	13,935
5th quintile								
Proxy	45.22***	42.56***	–0.95**	0.49	–31.67***	–7.19***	–7.27***	–3.82***
	(3.06)	(4.01)	(0.42)	(0.66)	(2.66)	(0.93)	(1.29)	(0.65)
Difference (%)	81.02	12.78	24.54	16.83	11.49	30.29	14.56	24.61
Average time reported by self (in min)	55.81	332.97	3.87	2.91	275.51	23.73	49.93	15.52
Observations	13,738	13,616	13,738	13,616	13,738	13,616	13,738	13,616
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: for details on controls, refer to Table 4. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Source: authors' compilation based on TUS19.

Table A6: IPW estimates of time use reported (15–64 years) by region

	Employment activity (in min)		Production for self-consumption (in min)		Unpaid domestic work (in min)		Unpaid care work (in min)	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)
North region								
Proxy	15.46***	38.10***	–4.03***	–10.55***	–25.23***	–11.08***	–4.19***	–0.18
	(2.13)	(3.14)	(1.26)	(1.18)	(2.04)	(0.74)	(0.97)	(0.42)
Difference (%)	28.02	11.85	8.32	25.65	8.47	40.73	9.95	1.90
Average time reported by self (in min)	55.16	321.49	48.38	41.12	297.83	27.20	42.11	9.43
Observations	23,503	24,829	23,503	24,829	23,503	24,829	23,503	24,829
Southern region								
Proxy	49.67***	30.25***	3.07***	2.20***	–20.92***	–8.93***	–12.86***	–1.20***
	(2.63)	(2.64)	(0.67)	(0.78)	(1.77)	(0.59)	(0.83)	(0.39)
Difference (%)	44.35	8.82	27.63	15.98	8.02	33.76	28.24	10.61
Average time reported by self (in min)	111.99	342.75	11.11	13.76	260.61	26.45	45.53	11.30
Observations	34,385	32,567	34,385	32,567	34,385	32,567	34,385	32,567
Western region								
Proxy	53.94***	42.75***	–4.86***	–3.99***	–31.67***	–7.95***	–8.83***	–1.78***
	(2.85)	(2.93)	(0.78)	(0.79)	(2.08)	(0.72)	(0.92)	(0.43)
Difference (%)	54.09	12.19	23.94	23.25	10.74	31.41	20.81	15.22
Average time reported by self (in min)	99.72	350.69	20.30	17.16	294.79	25.31	42.42	11.69
Observations	24,477	25,715	24,477	25,715	24,477	25,715	24,477	25,715
Eastern region								
Proxy	10.14***	46.59***	–4.78***	–14.57***	–9.70***	–9.65***	–0.92	–2.25***
	(1.77)	(2.42)	(0.68)	(0.94)	(1.83)	(0.72)	(0.93)	(0.43)
Difference (%)	25.11	14.94	19.47	36.74	2.79	23.54	1.70	12.79
Average time reported by self (in min)	40.38	311.71	24.55	39.65	346.70	40.98	54.11	17.59
Observations	33,799	33,957	33,799	33,957	33,799	33,957	33,799	33,957
Central region								
Proxy	4.16**	59.13***	–4.57***	–10.28***	–9.11***	–11.12***	–2.88***	–1.90***
	(1.69)	(2.57)	(0.95)	(1.32)	(1.70)	(0.70)	(0.74)	(0.33)
Difference (%)	7.67	22.47	10.95	15.45	3.07	30.75	6.78	17.82
Average time reported by self (in min)	54.20	263.09	41.70	66.51	296.42	36.16	42.42	10.66
Observations	36,864	38,055	38,181	38,055	38,181	38,055	38,181	38,055
North-eastern region								
Proxy	28.64***	22.98***	2.95	–2.22	–44.68***	–8.81***	–15.43***	–3.32***
	(3.25)	(3.31)	(1.80)	(1.81)	(2.62)	(1.14)	(1.55)	(0.65)
Difference (%)	35.70	9.14	6.80	3.19	13.20	13.67	23.76	15.44
Average time reported by self (in min)	43.59	251.23	43.38	69.52	338.26	64.43	64.92	21.50
Observations	18,728	18,653	18,728	18,653	18,728	18,653	18,728	18,653
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: for details on dependent variable and controls, refer to Table 4. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. The northern region includes: J&K, Punjab, Haryana, Chandigarh, Delhi, Himachal Pradesh, Rajasthan. The southern region includes: TN, Andhra Pradesh, Kerala, Pondicherry, Karanataka, Lakshadweep, Telangana. The east region includes: Jharkhand, Orrisa, WB and Bihar. The western regions includes: Gujarat, Maharashtra, Goa, and union territories such as Daman and Diu, Dadar Nagar Haveli. The central region includes: MP, Uttrakhand, UP, Chattisgarh. The north-eastern region includes: Assam, Arunachal Pradesh, Manipur, Tripura, Meghalaya, Mizoram, Nagaland.

Source: authors' compilation based on TUS19.

Table A7: Lasso results for time use

	Employment activity		Production for self-consumption		Unpaid domestic work		Unpaid care work	
	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
Proxy	17.59***	42.93***	–2.85***	–9.31***	–16.12***	–10.22***	–6.95***	–1.88***
	(0.73)	(1.11)	(0.44)	(0.53)	(0.81)	(0.34)	(0.40)	(0.19)
Average time reported by self (in min)	76.85***	357.03***	30.07***	38.28***	312.62***	35.17***	50.92***	14.55***
	(0.46)	(0.78)	(0.23)	(0.35)	(0.43)	(0.24)	(0.25)	(0.13)
N	153,608	149,504	153,608	149,504	153608	149,504	153,608	149,504

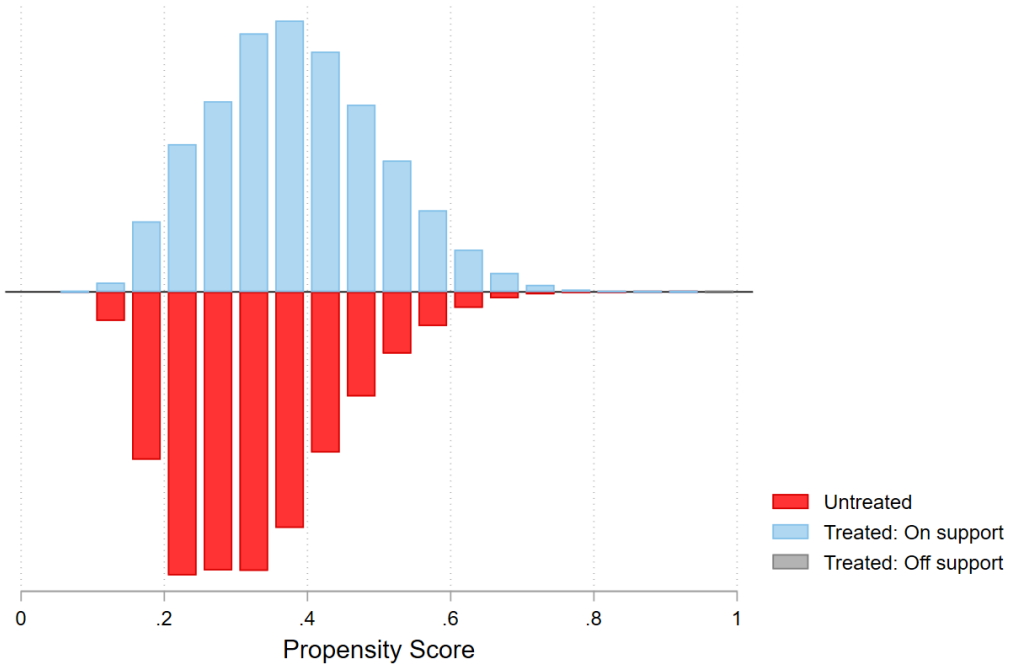
Note: for details on controls, refer to 4. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: authors' compilation based on TUS19.

Table A8: PSM and IPW estimates of time use reported (15–64 years) with day of week fixed effects

	Employment activity (in min)		Production for self-Consumption (in min)		Unpaid domestic work (in min)		Unpaid care work (in min)	
	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
Closest match								
Proxy	16.28***	41.62***	–2.59***	–8.56***	–12.11***	–9.93***	–8.04***	–1.66***
	(1.02)	(1.37)	(0.54)	(0.63)	(1.01)	(0.41)	(0.54)	(0.23)
Difference (%)	21.44	11.90	8.52	19.47	3.80	27.86	16.01	11.90
IPW								
Proxy	16.39***	41.95***	–2.40***	–8.96***	–11.92***	–9.96***	–7.03***	–1.85***
	(0.75)	(1.11)	(0.45)	(0.54)	(0.80)	(0.34)	(0.42)	(0.20)
Difference (%)	21.58	11.99	7.90	20.38	3.74	27.95	14	13.27
Average time reported by self (in min)	75.93	349.69	30.37	43.96	318.09	35.63	50.19	13.94
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	153,605	149,501	153,605	149,501	153,605	149,501	153,605	149,501

Note: for details on controls, refer to Table 4. Standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: authors' compilation based on TUS19.

Figure A1: Common support for PSM



Note: a common support ensures sufficient overlap in the characteristics of treated (proxy) and untreated (self) groups to find adequate matches. In our analysis, there is a near to perfect common support (only four treated units could not be matched with control).

Source: authors' compilation based on TUS19.