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COVID-19 and the changing profiles of poverty in India: A fuzzy set analysis and imputation approach using PLFS data

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A B S T R A C T

This paper has the double aim of contributing to the debate on poverty in India by looking at the changing poverty profiles during the pandemic and addressing the challenges posed by the longstanding data limitations for poverty analysis. We use a fuzzy-set methodology to assess the changes in poverty characteristics over time and a stochastic multiple imputation method to enhance the accuracy of the PLFS data. Our analysis encompasses both consumption- and income-based poverty, with a focus on historically marginalised groups such as children and women. We find that the post-shock economic recovery period seems to have bypassed these groups, leaving them struggling to improve their circumstances. In the consumption-based analysis, poverty is rising among larger households and casual labourers, while in the income-based analysis, households with children and working-age women are increasingly affected, with a growing gender disparity and a strong association with low-skilled jobs.

1. Introduction

In 2020, the world witnessed an unprecedented surge in global poverty and inequality, as the COVID-19 pandemic inflicted severe socio-economic consequences marking a significant setback for sustainable development goals (SDG). The non-pharmaceutical interventions (NPI) introduced to combat the spread of the SARS-CoV-2 virus, such as social distancing guidelines, business closures, and school shutdowns, had a profound and far-reaching impact on labour markets, posing significant threats to families and children, especially those living in the most impoverished households [1,2].

Following the impact of COVID-19, a new group of individuals has emerged—those who were not previously considered poor but have fallen into poverty due to the pandemic. This phenomenon reflects the "changing profiles of poverty" in the country, as the crisis has changed the economic landscape. This shift highlights the mutability of economic systems and underscores the need for resilient, sustainable frameworks to safeguard against such shocks. This paper aims to employ robust measurement methodologies to analyse the trends and determinants of new poverty in India during the COVID-19 pandemic, taking into account the uncertainties of the available data. Specifically, by employing advanced statistical tools, we seek to answer the following research questions: what are the characteristics of the new poverty profiles? Which types of occupations were most affected? Was there a differentiated impact for households with children or working-age women? This analysis is critical for informing sustainable policy responses that consider the long-term social dimensions of recovery and resilience. Moreover, it is indicative of how people in vulnerable situations are exposed to various shocks, such as those related to pandemics and climate/environmental changes.

India experienced the full impact of the pandemic's socio-economic disruptions. The country saw a sharp spike in levels of unemployment and substantial job losses and witnessed a large wave of internal migration as individuals sought refuge in rural areas [3]. After the initial shock in 2020, the country experienced a recovery in terms of jobs and GDP, followed by fluctuations [3,4]. However, given the heterogenous effects of the shocks, it is unclear which groups have recuperated, to what extent they have recovered, and whether the cumulative impact of shocks has disrupted previous improvements.

Our study helps to clarify these aspects, contributing to the literature on the impacts of COVID-19 on poverty and the debate on poverty measurement in India [5,6]. However, studying poverty in India presents challenges due to a long statistical gap. Using the Periodic Labour Force Survey (PLFS), we attempt to reduce the data limitations and

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report uncertainties by estimating monetary poverty with both consumption-based and labour-income-based specifications, employing a fuzzy-set approach [7], and implementing a stochastic multiple imputation method to adjust for rounding errors presented in the PLFS consumption expenditure data [8,9].

Our study innovates in four main ways. First, we contribute to the ongoing and highly engaged debate on poverty measurement and levels in India by employing a fuzzy-set approach, treating poverty as a matter of degree, and implementing a stochastic multiple imputation method to correct rounding errors in the PLFS consumption expenditure variable. These methods have not been previously applied within the context of the ongoing debate in India. Second, we offer a comprehensive exploration of monetary poverty in India by considering two distinct perspectives: consumption-based and labour-income-based. Third, we contribute to the empirical literature on the impact of the pandemic on poverty in India, specifically focusing on understudied households with children. Lastly, our study investigates heterogeneous effects between labour-related variables and the number of children and working-age women in households. This study is linked with the objectives of the United Nations Sustainable Development Goals (SDGs), specifically, it tracks Goal 1 on "no poverty," Goal 5 on "gender equality", and Goal 8 on "decent work and economic growth."

The structure of the paper is as follows. Section 2 reviews the methods and literature on poverty measurement in India in the context of the statistical gap. Section 3 details the data and methods, explaining the challenges and limitations. Section 4 presents the results for the main specification. Section 5 presents the results for the specification that uses an imputation method. Section 6 concludes.

2. Measuring monetary poverty in India

2.1. The debate on poverty measurement and levels after 2011-12

In India, monetary poverty is typically measured using consumption expenditure, with the primary data source being the Consumer Expenditure Survey (CES) from the National Sample Survey Organization (NSSO). This survey collects data on Monthly Consumer Expenditure (MPCE) through a detailed questionnaire on the consumption of different items.

The CES is intended to be conducted periodically at five-year intervals, but during the pandemic, the latest year of publicly available CES data was from 2011-12. To estimate poverty in this statistical gap, different methodologies such as extrapolation techniques [6,10], imputation methods, and alternative data sources like the Consumer Pyramids Household Survey (CPHS), the Survey on Social Consumption (SCS) on Health, the NSSO survey on Household expenditure on services and durable goods, and the Periodic Labour Force Survey (PLFS) have been used.

Extrapolation techniques used to be the official method of the World Bank to estimate poverty in the absence of official data in India [6],[1] though they produced contrasting poverty estimates (see [6,10]).[2] In addition to the national accounts-based technique, survey-to-survey imputation methodologies have also been used to estimate poverty [10]. Based on a small area estimation method, Edochie et al. impute the CES 2011–2012 household consumption expenditure into the SCS. Their approach is similar to Newhouse and Vyas [11].[3] Newhouse and Vyas [11] found that poverty (with a 1.90$ PPP poverty line) decreased in 2014–2015 compared to 2011–2012.[4]

An alternative data source is the CPHS, run by the Centre for Monitoring the Indian Economy, but it is not publicly available. While similar to the CES in recording detailed expenditures on various commodities, the CPHS data has limitations with little independent validation of its nature and quality.[5] To address some of the limitations of CPHS, Roy and van der Weide [12] employed a reweighting technique aiming to transform the survey into a nationally representative dataset. Their findings, which suggest poverty reduction between 2015 and 2019 was lower than national account projections, have become the official poverty level for India on the World Bank's Poverty and Inequality Platform [13,14].[6]

Finally, there are also attempts to measure poverty using the PLFS. This survey is appealing because it is a public survey that is nationally representative and provides the variable Usual Monthly Consumer Expenditure (UMPCE), which has been used as a proxy of consumption expenditure to measure poverty. However, there are doubts about whether it is appropriate to use the UMPCE to measure poverty because it is not based on a detailed questionnaire as in the CES. Mehrotra and Parida [15] use the UMPCE arguing that although it is not detailed as the consumption expenditure in the CES, it is possible to consistently estimate changes in consumption over time. Additional attempts to use this variable or to estimate poverty from PLFS include Mehrotra and Parida [16], where UMPCE is used as an instrumental variable leveraging its correlation with economic status to account for the household expenditure on education and skills development, and Himanshu, Lanjouw, and Schirmer [17] who contribute to the poverty estimates debate implement a survey-to-survey imputation procedure to transfer the EUS consumption aggregate into the PLFS surveys from 2017/18 to 2022/23 and apply redefined poverty lines to this imputed data to estimate poverty for each PLFS survey year.

Therefore, the limitations in the availability of data in India have produced a new debate[7] about methods to estimate poverty in the absence of official data and about the evolution and levels of poverty. There is no consensus about the best method or about the real poverty levels. Each method has advantages but also many assumptions and limitations.

2.2. Poverty during the COVID-19 pandemic

The statistical gap discussed above includes the period of the COVID-19 pandemic. Consequently, few studies cover that period and most of them are projections of potential scenarios. In addition, most of these studies do not attempt to correct the data or method issues discussed

[1] Basically, this method projects the available official data on consumption expenditure (e.g., CES 2011–2012, or other alternative survey) to more recent years by adjusting it with the national accounts data (i.e., growth of the nominal Private Final Consumption Expenditure).

[2] Bhalla, Bhasin and Virmani [6] improved this method by incorporating food subsidies, arguing that traditional estimates overstate poverty by not accounting for in-kind transfers. Using international poverty lines (1.9$PPP and 3.2$PPP), they found that poverty consistently decreased after 2011. Edochie et al. [10] also used an extrapolation method and the international poverty line of 1.9$PPP and found no increase in poverty between 2011-2012 and 2017–2018. However, national accounts data have limitations, including different collection methods and higher growth rates compared to household surveys, leading to potential underestimation of poverty levels [31,32].

[3] With the main difference being that the latter used the last three CES rounds (2004–2005, 2009–2010, and 2011–2012) to impute data into the NSSO survey on Household expenditure on services and durable goods.

[4] Edochie et al. [10] acknowledge that the imputation method may not account for important changes in the behaviour of markets between periods that are too far apart.

[5] Researchers have identified shortcomings, noting its underrepresentation of women, young children, and poor households, along with an overrepresentation of well-educated households [32–35].

[6] However, while acknowledging Roy and Weide's method as an advance, Drèze and Somanchi [36] demonstrate that it fails to correct the underrepresentation of poor households, concluding that the reduction in poverty between 2011 and 2019 has been overstated by the two authors.

[7] Some scholars refer to this discussion as the "Great Indian Poverty Debate 2.0" in reference to a previous debate in the 1990s. See Ghatak [37] for a series of articles and commentaries about this new debate.

above. Table 1 shows their poverty estimates.

Using an extrapolation technique, Bhalla, Bhasin and Virmani [6] found that poverty with the poverty line of 1.90$ PPP did not increase significantly during the pandemic, while with the poverty line of 3.20$ PPP estimated that poverty increased by almost 4 percentage points (pp) between 2019 and 2020. They argue that the Indian food subsidies policy helped to reduce the shocks. However, their analysis probably underestimates poverty because it does not adjust for the overestimation of consumption growth in the national accounts.

Using the CPHS, Basole et al. [3] estimated that poverty increased 15 pp in rural areas and 20 pp in urban areas between 2019 and 2020. But the study does not try to correct the CPHS sample problems of under-representation of some groups. Ram and Yadav [18] used the PLFS 2018–2019 to simulate different potential scenarios for 2020–2021 by contracting the level of household consumption by 5 % and 10 %. Their estimates projected an increase between 15.38 and 20.35 pp in rural areas and 10.96 and 14.28 pp in urban areas. Updating the Tendulkar[8] poverty line using the Consumer Price Index, Mehrotra and Parida [15] conclude that poverty levels are higher in 2019–2020 compared to the levels of 2011–2012 estimated using the CES. However, they compare results from surveys that are not fully comparable. Both studies make no procedure to adjust the problems with the PLFS consumption expenditure variable.

Saxegaard et al. [22] also used CPHs but applied Roy and van der Weide's correction method to estimate monthly poverty trends before and during the pandemic. They found that poverty increased severely during the lockdown periods in 2020, with a recovery by the end of 2021 to near pre-pandemic levels.

Recently, Salmeron-Gomez et al. [19] used data from various sources (e.g., Global Monitoring Database (GMD), Poverty and Inequality Platform (PIP), and GPD data) to forecast child poverty levels for 2022. They estimate that poverty levels for households with children in India are 11.5 % and 49.8 % with poverty lines of $2.15 PPP and $3.65 PPP respectively. World Bank [20] recently updated the PIP using the CPHS adjusted with Roy and van der Weide's method. Their estimations indicate an increase in poverty levels for both poverty lines of $2.15 PPP and $3.65 PPP in 2020, with a recovery in 2021. Nevertheless, the poverty rate with the $3.65 PPP poverty line is still higher than in 2019.

These ranges of different results illustrate substantial uncertainty around the true poverty levels in India. The consequences of this uncertainty are not limited to measurement. Without a clear understanding of the extent of poverty, it becomes difficult to determine the appropriate sustainable resources and strategies necessary to address the problem. In addition, the uncertainty is even higher for groups such as children, which remain understudied. Our paper tries to fill this gap, but instead of trying to estimate exact levels of poverty, it uses rigorous methods to effectively analyse trends and changes in determinants of poverty.

3. Data and methods

3.1. The Periodic Labour Force Survey (PLFS)

The ideal data to identify new groups of people who have fallen into poverty because of the pandemic would be a panel tracking the socio-economic conditions of households before, during, and after the COVID-19 crisis. However, as discussed in the preceding section, such data is not available in India. Given our emphasis on changes in poverty rather than absolute levels, we have chosen to analyse monetary poverty using repeated cross-sections from the Periodic Labour Force Survey (PLFS). This decision is based on four key considerations.

First, the PLFS is a public dataset that provides data on the Usual Monthly Consumer Expenditure (UMPCE) and earnings from regular salaried/wage, self-employed, and casual labour activities, enabling the estimation of poverty levels. Second, the survey spans the period before, during, and after the main COVID-19 pandemic shocks. Five rounds of annual data have been released based on data collected quarterly during July 2017–June 2018, July 2018–June 2019, July 2019–June 2020, July 2020–June 2021, and July 2021–June 2022[9]. The PLFS adopts a panel design with four visits to the same households. However, this panel data is only available for urban areas, and the usual consumption expenditure variable is only collected during the first visit. For our analysis, we use the data from the first visit, treating it as a repeated cross-section because it covers rural areas and includes the consumption expenditure variable.

Third, the PLFS provides detailed individual- and household-level data on many socioeconomic characteristics, which allows us to evaluate their relationship with monetary poverty in time. The National Statistical Office (NSO) launched the PLFS to provide data on employment- and unemployment-related indicators, but it also provides data on socio-demographic characteristics, level of education, labour income, and household usual consumption expenditure.

Fourth, the survey is nationally representative. As our focus lies on analysing poverty in households with children, it is essential that this subgroup is represented in the sample. For this reason, using the CPHS would not be suitable for our study as it could potentially bias the results.

Nevertheless, using the consumption expenditure variable of the PLFS to estimate poverty brings four important limitations to the analysis. These limitations are that the UMPCE is based on a small number of questions, the method of collecting the UMPCE has changed by asking more questions from the fourth round (2020-21), the UMPCE is subject to measurement error (i.e., rounding errors), and data collection was temporarily suspended during COVID-19. Appendix A details each of these limitations, highlighting their implications for our analysis.

Given the numerous limitations inherent in PLFS data, the following sections outline our proposed methodologies for mitigating these limitations and reporting uncertainties. Despite our efforts, we acknowledge that our findings are still subject to limitations, and we take them into account in our analysis.

3.2. The fuzzy set approach to poverty measurement

The first procedure we use to reduce the PLFS limitations is to estimate poverty considering both the household consumption expenditure per capita and household labour income per capita. The former specification is less subject to rounding errors and offers additional valuable information because it is an alternative perspective on poverty that focuses on working-poor individuals. Additionally, because wages and profits are not subject to smoothing mechanisms such as using savings to maintain consumption levels, we can observe short-term income fluctuations caused by the economic shocks during the pandemic.

To accurately estimate labour income poverty, we only consider a subsample of individuals who reside in households with at least one person in the labour force. This is because the PLFS does not gather information on income from other sources. If we were to consider the entire sample, we could mistakenly identify households as poor that have sources of income other than labour (e.g., pension, rents). Still, labour income is typically the primary source of income for most households. However, as with other labour surveys, labour income variables have limitations. Because self-employed and casual labour activities are uncertain and unstable, it is more difficult to track earnings accurately and their values may be collected with less precision. Therefore, poverty estimations may be biased, especially because these

[8] For more details about official poverty lines in India, refer to Planning Commission of India [21].

[9] At the time of writing this paper, the latest survey (PLFS 2023-2024, June 2024) had not yet been released.

Table 1
Poverty headcount ratio estimations in the literature, COVID-19 period.

Paper	Dataset	Poverty line	2018–19	2019	2019–20	2020	2021
Basole et al. [3]	CPHS (Rural)	Min. wage		25.4		41	
Basole et al. [3]	CPHS (Urban)	Min. wage		15.6		35.3	
Mehrotra and Parida [15]	PLFS	Tendulkar[1]			25.9		
Ram and Yadav [18]	PLFS	Rangarajan[1]	33.3			47.3–51.8	
Bhalla, Bhasin and Virmani [6]	CES + Nat. accounts	\$1.90 PPP		0.8–1.9		0.9–2.1	
Bhalla, Bhasin and Virmani [6]	CES + Nat. accounts	\$3.20 PPP		14.8–25.5		18.1–29.9	
Salmeron-Gomez et al. [19]	PIP + UNDESA + GPD (Child)	\$2.15 PPP				11.5	
Salmeron-Gomez et al. [19]	PIP + UNDESA + GPD (Child)	\$3.65 PPP				49.8	
World Bank [20]	CPHS (reweighted)	\$2.15 PPP		12.7		14.7	11.9
World Bank [20]	CPHS (reweighted)	\$3.65 PPP		45.9		49.7	46.5

Notes: 1. For more details about official poverty lines in India, refer to the Planning Commission of India [21]. Saxegaard et al. [22] did not present poverty levels in their study.

groups tend to be more at risk of being in poverty.

All monetary values are adjusted for inflation using the Consumer Price Index (CPI) by area type (rural and urban) and by state. In this way, we ensure comparability over time and account for varying cost-of-living differences that may affect purchasing power differently across area types and states. To calculate per capita values and the number of people in each household, we excluded servants, employees, and other members. To maintain comparability across rounds, we also excluded temporary visitors, as information about this group is only available in the fourth round (2020–2021).

To reduce the data limitation, we estimate poverty using a fuzzy set approach, which considers poverty as a matter of degree rather than a binary phenomenon (i.e., poor/non-poor) [23]. As such, there is no need to set poverty thresholds because poverty membership degrees are determined according to the individual's relative position in the distribution. Every unit of the sample will belong to the fuzzy set of poverty to a certain degree that ranges from zero for the unit at the top of the distribution to one for the unit at the bottom of the distribution. In this way, we avoid arbitrarily setting a poverty line in the context of imprecise consumption expenditure values. Moreover, we reduce the bias caused by incorrectly assigning households as poor or non-poor due to measurement errors such as rounding errors.

To calculate the fuzzy poverty degrees, we follow the Integrated Fuzzy and Relative (IFR) approach proposed by Betti et al. [7]. Because we want to analyse trends, we adapted the membership degree to ensure comparability across years. That is, we pool the individuals from the survey rounds of interest to determine their relative distribution positions considering all the periods together. The resulting membership function of the pooled fuzzy indicator is the following:

$$m_{it} = [1 - F(X_{it})]^{\alpha-1}[1 - L(X_{it})] = \left(\frac{\sum_{\gamma} w_{\gamma} \mid X_{\gamma} > X_{it}}{\sum_{\gamma} w_{\gamma} \mid X_{\gamma} > X_{1}}\right)^{\alpha-1}\left(\frac{\sum_{\gamma} w_{\gamma}X_{\gamma} \mid X_{\gamma} > X_{it}}{\sum_{\gamma} w_{\gamma}X_{\gamma} \mid X_{\gamma} > X_{1}}\right) \tag{1}$$

where, for each individual i and time range t, X is the UMPCE or labour income per capita, F is a cumulative distribution function, L is a function to determine Lorenz curve values, ω_{γ} is the individual sample weight ranked by γ,and α is a parameter. Usually, to facilitate comparisons among poverty measures, α is set in a way such that the mean of the membership function is equal to the poverty headcount ratio. Because there is no precise estimation of the incidence of poverty in India and because our interest lies in trends, we do not make such a comparison. Instead, we set $\alpha = 2$, leading to an elevation of one.

3.3. Imputation method to adjust the rounded consumption expenditure data

To ensure that our results are robust, we estimate two alternative poverty measure specifications based on the headcount ratio with the \$2.15 PPP international (extreme) poverty line. In addition, to model the uncertainties of the consumption data, we use a multiple imputation method to correct the rounding error of the UMPCE. This imputation models the consumption distribution and the heaping behavior, producing multiple values that capture potential "true consumption values". We have, therefore, two alternative measures: the income-based headcount ratio (IHCR), and the multiple potential consumption-based headcount ratio (MCHCR).

The variable on consumption expenditure and the variables that are used to build it are affected by heaping. In addition, the extent of the rounding intervals is unknown, meaning that different households reported an approximation of their true consumption expenditure values, and this approximation varies among households. To correct for these rounding errors, we use a stochastic multiple imputation based on the method proposed by Drechsler and Kiesl [9] and Van der Laan and Kuijvenhoven [8]. Using imputations has advantages, such as accounting for uncertainty, generating valid statistics, and obtaining estimates with the average of multiple imputed outcomes.

The approach estimates rounding probabilities given the observed rounded variable and imputes the "true" value by modelling the consumption expenditure distribution given observed covariates. To model the distribution of the household consumption expenditure (Y), we assume that it follows a log-normal distribution controlled by observed covariates (X):

$$log(Y) \mid X \sim N(X'\beta, \sigma^2) \tag{2}$$

where, for each household, X is a set of observable controls such as share of employed, equivalized number of members, household labour characteristics, and maximum level of education, β are the coefficients, and σ^2 the standard error.

To account for the rounding behaviour, we assume that the rounding degrees take the values of Rs. 500, Rs. 1000, or Rs. 2000. To model it, we assume that the latent variable G is normally distributed and dependent on the log of the observed consumption expenditure value:

$$G \mid log(Y) \sim N(\gamma_0 + \gamma_1 \, log(Y), \tau^2) \tag{3}$$

where γ_0 is the constant, γ_1 is the coefficient, and τ^2 the standard error.

Using a maximum likelihood estimation, the next step is to calculate the set of parameters from their joint posterior distribution of (2) and (3). Using these parameters, the imputation algorithm follows a rejection sampling approach given the plausible rounding values. Imputed values are created only for individuals who are likely to have rounded consumption expenditure. To perform the multiple imputations, we used the package *hmi* from the statistical software R (see [24]).

We run the model for each plausible value separately, generating five imputed variables, which gives us fifteen new variables. The imputations for the fourth and fifth PLFS rounds are done separately for each of the five variables that form the UMPCE. Therefore, to calculate the final imputed values of UMPCE, we randomly pick the imputed values for each consumption variable and each rounding degree to create fifteen imputed variables. When using variables with imputed values, our inference estimations follow Rubin's rule [25], which allows us to have valid statistics.

The imputation method to adjust for rounding errors is not without limitations. There are other plausible rounding degrees not covered by our model, and the model is subject to misspecifications (e.g., rounding values, and model covariates). However, because the imputation produces new values only for people likely to have rounded data, the model is less sensitive to misspecification. In any case, rather than finding the exact values of poverty, our intention here is to model and report the uncertainties of our data, produce valid inferences and, consequently, enhance our characterisation of poverty trends.

3.4. Empirical strategy

To understand which groups are the most vulnerable to shocks and how the characteristics of people in poverty have changed during the pandemic, we use fractional regressions to estimate determinants of monetary poverty conditional on socioeconomic characteristics and geographic controls.

Fractional regression is appropriate because our dependent variables are bounded between 0 and 1 and may be equal to 0 or 1 [26]. The model is fitted by the method of quasi-maximum likelihood, and, to ensure that the predictions of means are also bounded between 0 and 1, it uses the probit or logit model.

In our specification, we run fractional probit regressions comparing each PLFS round from 2018-19 until 2021-22 by rural and urban areas. Our base model is denoted as follows:

$$E(y_{it} | X_{it}, Z_{it}, c_i) = \Phi(\beta X_{it} + \delta Z_{it} + c_i) \tag{4}$$

where i is the household and t the year; y is the poverty fuzzy degree estimated using the UMPCE or the labour income; X is a vector of observable controls of interest such as demographic and socioeconomic characteristics of households; Z is a vector of other observable controls such as social groups and regions; α is the constant; β and δ are the model coefficients, and Φ is the normal distribution's cumulative distribution function. We estimate all the outcomes using sampling weights taking account of the survey design.

For the alternative specification that estimates headcount ratio (with an imputation method for the consumption-based poverty), we estimate probit regressions using the same covariates, but the dependent variable is the average of the multiple potential consumption-based headcount ratios (MCHCR) and the income-based headcount ratio (IHCR). The model is the following:

$$P(Y_{it} = 1 | X_{it}, Z_{it}) = \Phi(\beta X_{it} + \delta Z_{it}) \tag{5}$$

where i is the household and t the year; Y is the MCHCR or the IHCR; X is a vector of observable controls of interest such as demographic and socioeconomic characteristics of households; Z is a vector of other observable controls such as social groups and regions; β and δ are the model coefficients, and Φ is the cumulative standard normal distribution function. We estimate all the outcomes using sampling weights taking account of the survey design, and, for the MCHCR the inference estimations follow the Rubin's rule [25], which pool parameter estimates.

To analyse heterogenous effects between labour-related variables and the number of children or the number of working-age women in the household, we estimate predictive margins of their interactions. Unlike the base model, in this specification with interactions, we group children into a single category (i.e., less than 18 years old).

4. Results

In this section, we present the results of our empirical investigation. We begin our analysis by assessing poverty trends and applying fractional probit regressions using the fuzzy approach, which is helpful in identifying the characteristics of the changing poverty profiles. We first employ the fuzzy consumption-based poverty measure and then the fuzzy income-based poverty measure.

We conduct the regressions for each survey year separately, breaking down the sample between rural and urban households. The primary objective is to determine whether there is a significant change in the determinants of poverty during the pandemic years, such that it becomes necessary to examine the characteristics of individuals at risk of poverty through a new lens.

4.1. Fuzzy poverty degrees: trends and determinants

a) Fuzzy consumption-based poverty

To understand poverty trends before, during, and after the main pandemic shocks (2020q1, 2021q2, and 2022q1), we plotted the consumption-based fuzzy poverty outcomes ratio by quarters and by area type (Fig. 1). We can observe that households (HH) with children are on average much poorer than those without children. In rural areas, poverty is temporarily increased after the first shock, recovering fast until the second shock. After that, poverty levels remain roughly stable. Whereas in urban areas, the increase in poverty levels after the first shock was not temporary. For families with children, poverty levels remain stable after the first shock. For families without children, there is a recovery after the second shock, returning to pre-pandemic levels. Therefore, the pandemic shocks broke the downward-sloping trend of poverty, and households with children had more difficulty recovering from them.

Table 2 presents an analysis of the determinants of consumption-based poverty, categorized by PLFS rounds and area types based on Equation (4). The values in bold represent coefficients that are statistically significantly different from their corresponding coefficient in the pre-pandemic year (2018-19).[10]

Overall, the signs of the coefficients remain generally consistent across various years and area types, but there are notable variations in their magnitudes. Children exhibit stronger associations with poverty in comparison to working-age men and women, as well as the elderly population. Furthermore, within the distinct subgroups of children, children 0–5 years old show the highest association with poverty, followed by older age categories of children.

By comparing the evolution across the years, the association with poverty increased for most of the generational subgroups in 2020–21, with a recovery in 2021-22 that was not enough to return to pre-pandemic levels. The coefficients are either statistically significantly higher (especially in urban areas) or not statistically significantly

[10] To assess the significance of coefficient changes across years, in all specifications, we pooled each survey data with the initial period (2018-19), introduced a year dummy, and interacted it with all explanatory variables.

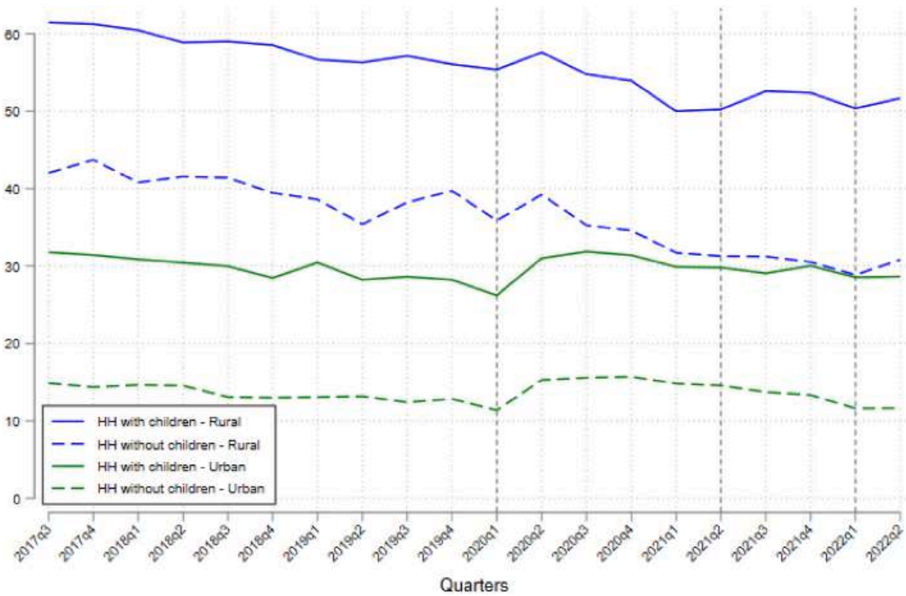

Fig. 1. Fuzzy consumption-based poverty trends by quarter. Notes: Outcomes are degrees of poverty. The three vertical dotted lines represent the main COVID-19 shocks when non-pharmaceutical interventions (NPI) took place in India.

Table 2
Fractional probit regressions average marginal effects, consumption-based poverty.

Y= Fuzzy consumption-based poverty	Rural				Urban			
Variables	2018–19	2019–20	2020–21	2021–22	2018–19	2019–20	2020–21	2021–22
# of working-age men (16–59)	0.033[a]	0.036[a]	**0.044**[a]	**0.041**[a]	0.025[a]	0.029[a]	**0.035**[a]	0.029[a]
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
# of working-age women (16–59)	0.026[a]	0.032[a]	**0.036**[a]	**0.036**[a]	0.029[a]	**0.037**[a]	**0.042**[a]	0.034[a]
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
# of elderly (>59)	0.037[a]	0.030[a]	0.036[a]	0.035[a]	0.026[a]	0.030[a]	**0.036**[a]	0.029[a]
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
# of child (0–5)	0.079[a]	**0.071**[a]	**0.086**[a]	0.082[a]	0.062[a]	0.057[a]	**0.070**[a]	0.059[a]
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
# of child (6–14)	0.074[a]	0.071[a]	0.077[a]	0.076[a]	0.053[a]	0.052[a]	**0.062**[a]	**0.057**[a]
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
# of child (15–17)	0.053[a]	**0.043**[a]	0.057[a]	0.052[a]	0.037[a]	0.034[a]	0.040[a]	0.039[a]
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Max education level in the HH	−0.014[a]	−0.014[a]	**−0.012**[a]	**−0.012**[a]	−0.017[a]	−0.015[a]	**−0.015**[a]	**−0.014**[a]
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Share of employed in the HH	−0.076[a]	−0.086[a]	−0.084[a]	**−0.126**[a]	−0.103[a]	−0.092[a]	**−0.060**[a]	−0.089[a]
	(0.011)	(0.013)	(0.010)	(0.010)	(0.010)	(0.012)	(0.009)	(0.008)
Family composition (base = One-adult household)								
Couples	0.023[a]	**0.044**[a]	**0.046**[a]	0.032[a]	0.019[b]	0.032[a]	**0.038**[a]	**0.039**[a]
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
Joint family	0.066[a]	**0.093**[a]	**0.094**[a]	0.082[a]	0.060[a]	0.061[a]	**0.081**[a]	**0.084**[a]
	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)
HH labour characteristic (base = regular wage earning)								
Self-employed in agriculture	0.089[a]	0.081[a]	**0.041**[a]	**0.030**[a]				
	(0.006)	(0.006)	(0.006)	(0.006)				
Self-employed in non-agriculture	0.052[a]	0.042[a]	0.045[a]	**0.033**[a]	0.032[a]	0.036[a]	0.031[a]	**0.023**[a]
	(0.007)	(0.008)	(0.007)	(0.006)	(0.003)	(0.004)	(0.004)	(0.003)
Casual labour in agriculture	0.134[a]	0.127[a]	0.125[a]	0.123[a]				
	(0.008)	(0.010)	(0.009)	(0.008)				
Casual labour in non-agriculture	0.103[a]	0.096[a]	0.089[a]	0.099[a]	0.086[a]	0.072[a]	0.090[a]	0.092[a]
	(0.007)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Others	0.046[a]	0.038[a]	0.069[a]	0.037[a]	−0.002	−0.006	0.007	−0.001
	(0.010)	(0.011)	(0.011)	(0.011)	(0.008)	(0.010)	(0.007)	(0.007)
HH main occupation (base = High skill jobs)								
Low skill	0.070[a]	0.054[a]	0.058[a]	**0.052**[a]	0.070[a]	**0.060**[a]	**0.056**[a]	**0.050**[a]
	(0.006)	(0.008)	(0.006)	(0.007)	(0.003)	(0.004)	(0.004)	(0.004)
Social group control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55,739	55,222	55,375	55,844	45,473	44,930	44,862	45,631

Notes: Linearized standard errors in brackets (taking account of the survey design).
Coefficients in bold are statistically significantly different from their corresponding 2018-19 values at $p < 0.1$ or lower.
[a] $p < 0.01$.
[b] $p < 0.05$.

different from 2018-19. These results suggest that households with many members became more vulnerable during the pandemic or their association with poverty remained stagnant.

The results from the family composition subgroups, namely couples and joint households, exhibit positive and statistically significant associations with consumption-based poverty that increased with the pandemic. Both couples and joint households are more at risk in rural than urban areas. However, poverty in urban areas for these groups did not recover in 2021–22, remaining statistically significantly higher than the pre-pandemic year.

In terms of HH-predominant labour characteristics, casual labour is the subgroup most strongly associated with consumption-based poverty. However, their coefficients do not exhibit any relevant changes in the magnitude during the pandemic. The association between self-employment and poverty showed a declining trend. This trend may be explained by workers who, after losing formal sector jobs, had to turn to self-employment as a survival strategy. This shift likely brought in more skilled workers or those with better coping strategies/capacities, which may have reduced the link between self-employment and consumption-based poverty. However, further research is needed to confirm this hypothesis and better understand the reasons behind this declining trend.

As for the estimates for occupation classification, households with low-skill jobs as their main occupation slightly narrowed the gap relative to households with high-skill jobs in the period. The differences between 2021-22 and 2018-19 are statistically significant for both rural and urban areas. This result is possibly due to various factors such as government support programmes, changing labour market dynamics, or other economic shifts.

b) Fuzzy income-based poverty

Fig. 2 depicts the trends for the fuzzy labour income poverty. In this specification, HH with children are on average also much poorer than those without. Unlike consumption-based poverty, the curves do not exhibit a downward-sloping trend in the initial period, implying that the situation was not improving before the pandemic. Following the initial shock, there is a substantial increase in poverty, particularly evident for households with children and urban areas. The impact of the first shock on poverty is more pronounced compared to consumption-based poverty, indicating that households may have relied on consumption-smoothing mechanisms to cope with the crisis.

In the second half of 2020, there was a swift recovery until 2021, followed by a subsequent poverty increase during the second shock. After that, rural areas saw a slow recovery, while urban areas experienced a more rapid one. However, when comparing the degree of poverty in the final and pre-pandemic quarters, there is not much improvement in poverty degree levels.

Table 3 shows the determinants of labour income poverty. Notably, a distinct gender disparity emerges within this specification. The number of working-age men is negatively associated with poverty while, conversely, there is a positive association between the number of working-age women and poverty. An analysis of these two subgroups over time shows that this gender-based gap has widened. These results reflect the low dynamism of the labour market for women in India, underscored by their low participation rate in the labour force (see [27, 28]).

Similar to consumption-based poverty estimates, the number of children is positively associated with poverty. However, during the pandemic, this association intensified for all age groups in both rural and urban settings. These increases were statistically significant for most subgroups compared to the pre-pandemic period.

Another difference with consumption-based poverty is that in urban settings, couples and joint families now display a negative association with poverty, although this effect tends to diminish over time. Conversely, in rural areas, joint families show a positive association with poverty, which surged during the pandemic but experienced a slight recovery in the most recent period. In this subgroup, the different signs between urban and rural areas during the main shock periods may suggest that in urban settings co-residence represented a safety net. One possible explanation is that while many urban workers lost jobs due to lockdowns and business closures, the diverse income opportunities available in cities provided a buffer for households with more dependents, making joint families more resilient to labour market disruptions. In rural areas, job opportunities were more limited, and many households relied solely on agriculture. Disruptions in the agricultural value chain and difficulties in the agricultural sector meant that, even with more household members, the overall income might not have been sufficient to avoid falling into poverty.

Regarding HH labour characteristics, subgroups labelled as "others," and "casual labour" showed the strongest association with poverty. Compared to the initial period, the association with poverty increased for the self-employed in urban areas in 2019-20 and 2020-21, with a

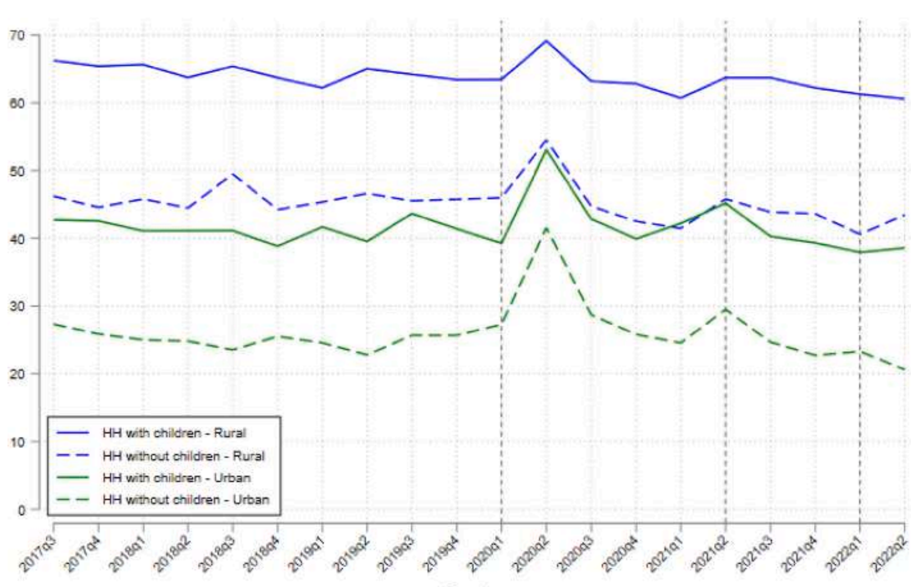

Fig. 2. Fuzzy income-based poverty trends by quarter. Notes: Outcomes are degrees of poverty. The three vertical dotted lines represent the main COVID-19 shocks when non-pharmaceutical interventions (NPI) took place in India. The sample is restricted to households that have at least one person in the labour force.

Table 3
Fractional probit regressions average marginal effects, income-based poverty.

Y= Fuzzy income-based poverty	Rural				Urban			
Variables	2018–19	2019–20	2020–21	2021–22	2018–19	2019–20	2020–21	2021–22
# of working-age men (16–59)	−0.027[a]	**−0.007**	−0.029[a]	−0.018[a]	−0.031[a]	−0.019[b]	−0.026[a]	**−0.013**[a]
	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)	(0.008)	(0.006)	(0.005)
# of working-age women (16–59)	0.027[a]	0.032[a]	0.029[a]	**0.050**[a]	0.005	**0.022**[a]	**0.023**[a]	**0.044**[a]
	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.004)
# of elderly (>59)	0.037[a]	0.039[a]	0.032[a]	0.029[a]	0.015[b]	**0.036**[a]	**0.030**[a]	**0.047**[a]
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.005)
# of child (0–5)	0.057[a]	**0.071**[a]	**0.086**[a]	**0.079**[a]	0.030[a]	0.026[a]	**0.043**[a]	**0.061**[a]
	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
# of child (6–14)	0.049[a]	**0.070**[a]	**0.074**[a]	**0.075**[a]	0.024[a]	0.016[a]	**0.034**[a]	**0.051**[a]
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)
# of child (15–17)	0.054[a]	0.053[a]	**0.084**[a]	0.067[a]	0.031[a]	0.019[a]	0.027[a]	**0.045**[a]
	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)	(0.007)	(0.005)	(0.005)
Max education level in the HH	−0.009[a]	−0.007[a]	**−0.007**[a]	−0.009[a]	−0.017[a]	−0.018[a]	−0.016[a]	**−0.014**[a]
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share of employed in the HH	−0.326[a]	**−0.168**[a]	**−0.181**[a]	**−0.113**[a]	−0.631[a]	−0.553[a]	**−0.489**[a]	**−0.245**[a]
	(0.031)	(0.030)	(0.028)	(0.026)	(0.032)	(0.041)	(0.036)	(0.028)
Family composition (base = One-adult household)								
Couples	−0.083[a]	**−0.025**[c]	**−0.019**	**−0.015**	−0.178[a]	−0.158[a]	**−0.121**[a]	**−0.030**[b]
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.023)	(0.018)	(0.014)
Joint family	−0.028[c]	**0.052**[a]	**0.070**[a]	**0.062**[a]	−0.120[a]	−0.115[a]	**−0.065**[a]	**0.020**
	(0.017)	(0.018)	(0.018)	(0.018)	(0.017)	(0.024)	(0.021)	(0.016)
HH labour characteristic (base = regular wage earning)								
Self-employed in agriculture	0.130[a]	**0.091**[a]	**0.104**[a]	0.142[a]				
	(0.009)	(0.010)	(0.010)	(0.010)				
Self-employed in non-agriculture	0.076[a]	0.065[a]	0.062[a]	**0.053**[a]	0.039[a]	**0.070**[a]	**0.065**[a]	0.030[a]
	(0.009)	(0.011)	(0.010)	(0.009)	(0.005)	(0.009)	(0.006)	(0.005)
Casual labour in agriculture	0.205[a]	**0.167**[a]	0.188[a]	0.201[a]				
	(0.011)	(0.013)	(0.012)	(0.013)				
Casual labour in non-agriculture	0.156[a]	**0.122**[a]	**0.118**[a]	**0.117**[a]	0.148[a]	**0.172**[a]	0.164[a]	0.134[a]
	(0.010)	(0.014)	(0.011)	(0.010)	(0.010)	(0.012)	(0.009)	(0.008)
Others	0.343[a]	0.319[a]	0.369[a]	**0.540**[a]	0.407[a]	0.386[a]	**0.490**[a]	**0.694**[a]
	(0.017)	(0.020)	(0.022)	(0.009)	(0.026)	(0.046)	(0.019)	(0.011)
HH main occupation (base = High skill jobs)								
Low skill	0.077[a]	0.064[a]	0.089[a]	0.098[a]	0.083[a]	**0.057**[a]	0.080[a]	**0.102**[a]
	(0.009)	(0.011)	(0.010)	(0.011)	(0.006)	(0.011)	(0.006)	(0.005)
Social group control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,973	21,605	20,904	20,317	22,940	21,485	22,168	22,177

Notes: Linearized standard errors in brackets (taking account of the survey design). The sample is restricted to households that have at least one person in the labour force. Coefficients in bold are statistically significantly different from their corresponding 2018–19 values at $p < 0.1$ or lower.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

recovery in 2021–22. In the final period, only the "others" and "self-employed in agriculture" subgroups witnessed an increase in the association with poverty, but the difference with the initial period was statistically significant only for the former.

In terms of occupational classification, after a decline in the association with poverty for the "low skill" subgroup during the period of the first shock (2019-20), this association rebounded and even exceeded the pre-pandemic levels (2018-19). However, the difference between the initial (2018-19) and the final period (2021-22) is statistically significant only in urban areas.

4.2. Heterogenous effects: labour, children, and women

The objective of this subsection is to understand if, in the years of the pandemic, there is evidence of heterogeneous effects in groups that are at higher risk of poverty. Therefore, we present the results of the regressions that explore the interactions between labour-related variables and the number of children and working-age women within households. In Appendix B, we provide additional findings related to the classification of occupation subgroups.

In general, it is evident that a higher number of children or working-age women in a household is associated with a greater likelihood of experiencing poverty, regardless of the household labour-related characteristics.

a) Fuzzy consumption-based poverty

The next two figures show the interaction between HH-predominant labour characteristics within households and the number of children in rural (Fig. 3) and urban (Fig. 4) areas.

In the context of rural areas, when comparing the different labour categories, we observe that the association between poverty and casual labourers (in purple and green) remains consistently high and stable. Conversely, other categories (in blue, red and orange) have shown signs of improvement during the period under scrutiny. The effect is a widening gap between casual labour and the remaining categories in 2021–22. In urban areas, we do not observe relevant changes in heterogeneous effects. However, it is worth noting that the association with poverty has shown a slight increase between 2019-20 and 2020-21, particularly among casual labourers and families with three or more children. Although the association between households with children and poverty has somewhat recovered in the subsequent period, it is noteworthy that the levels have largely persisted at levels like those observed in the 2018-19 data.

Figs. 5 and 6 depict the interactions between the number of working-age women and the HH predominant labour characteristics, within rural and urban settings, respectively. There is a consistent trend in both settings: as the number of working-age women within households increases, there is also a corresponding increase in the risk of poverty. In

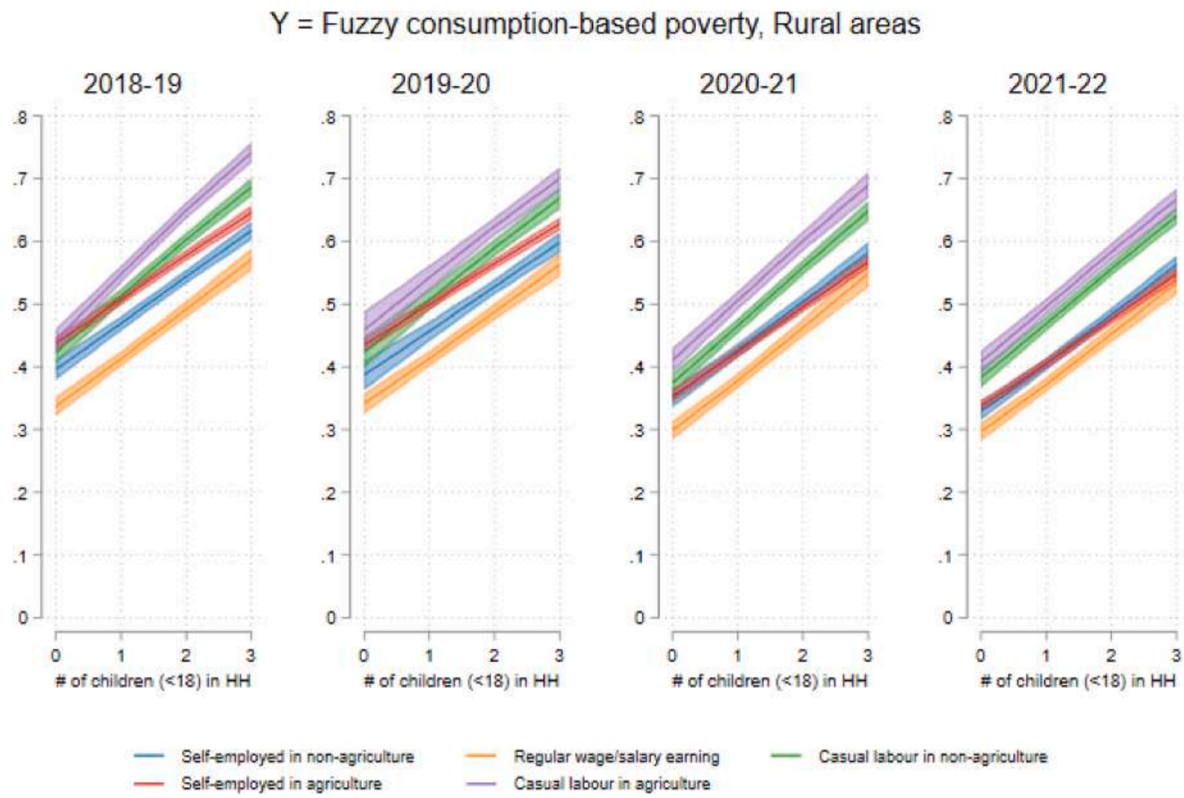

Fig. 3. Interaction between the number of children and HH labour characteristics, predictive margins, Rural areas. Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

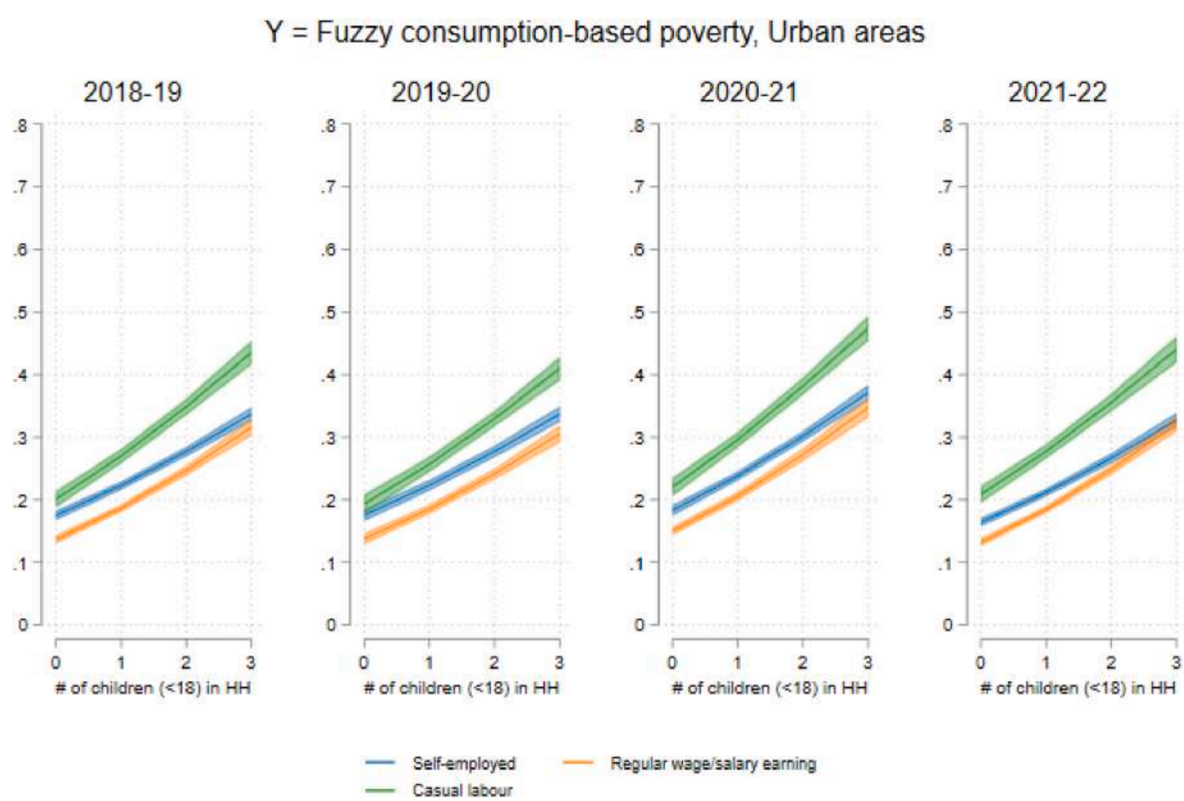

Fig. 4. Interaction between the number of children and HH labour characteristics, predictive margins, Urban areas
Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

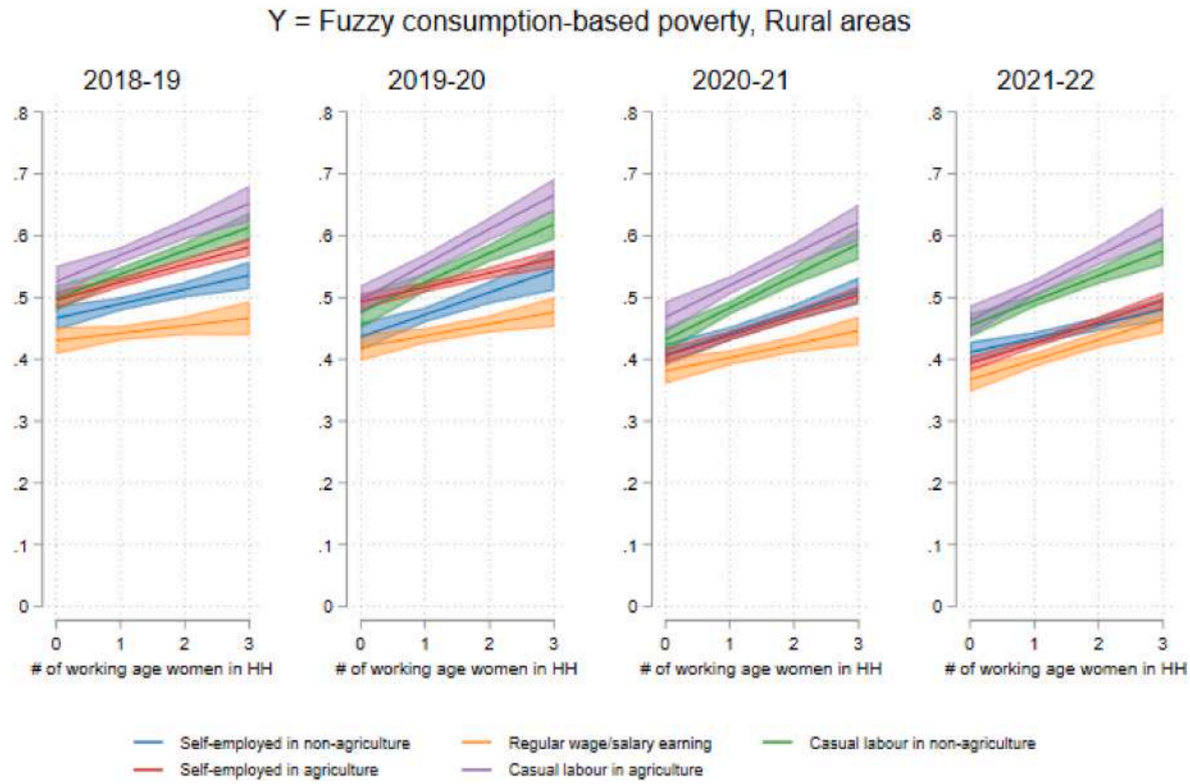

Fig. 5. Interaction between the number of working-age women and HH labour characteristics, predictive margins, Rural areas
Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

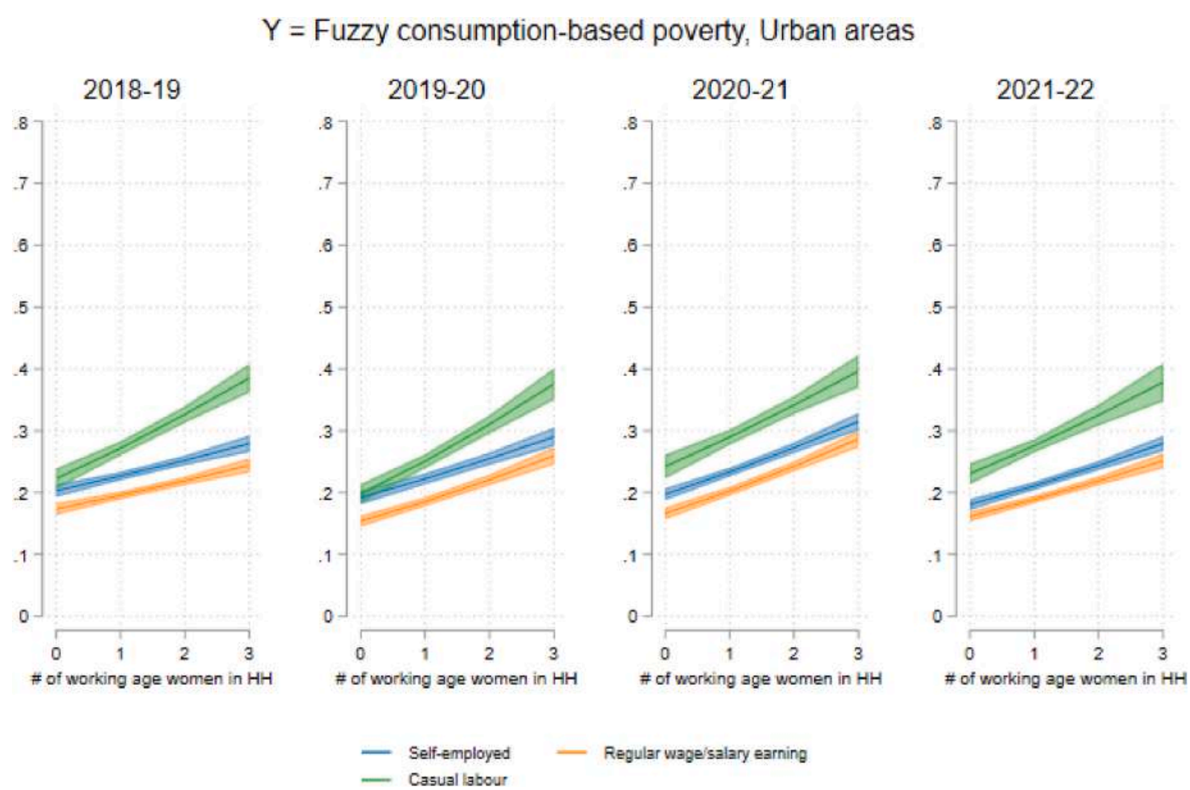

Fig. 6. Interaction between the number of working-age women and HH labour characteristics, predictive margins, Urban areas
Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

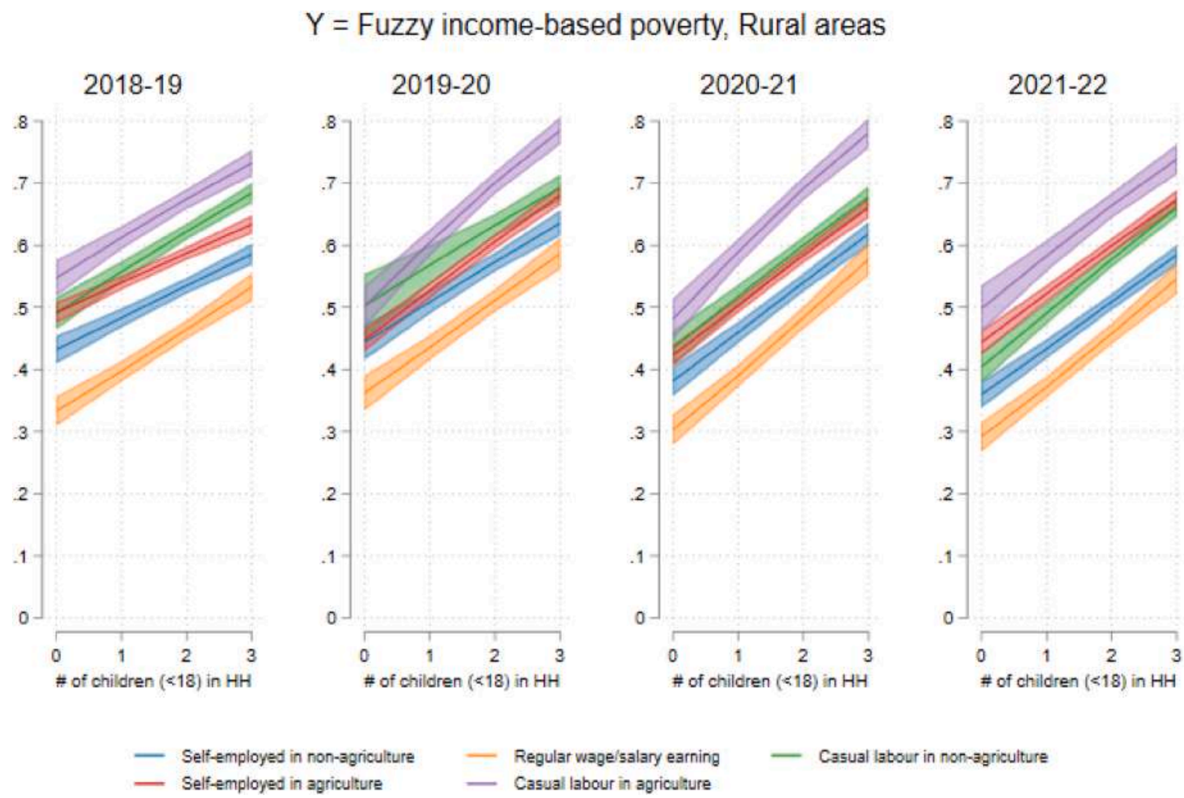

Fig. 7. Interaction between the number of children and HH labour characteristics, predictive margins, Rural areas
Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

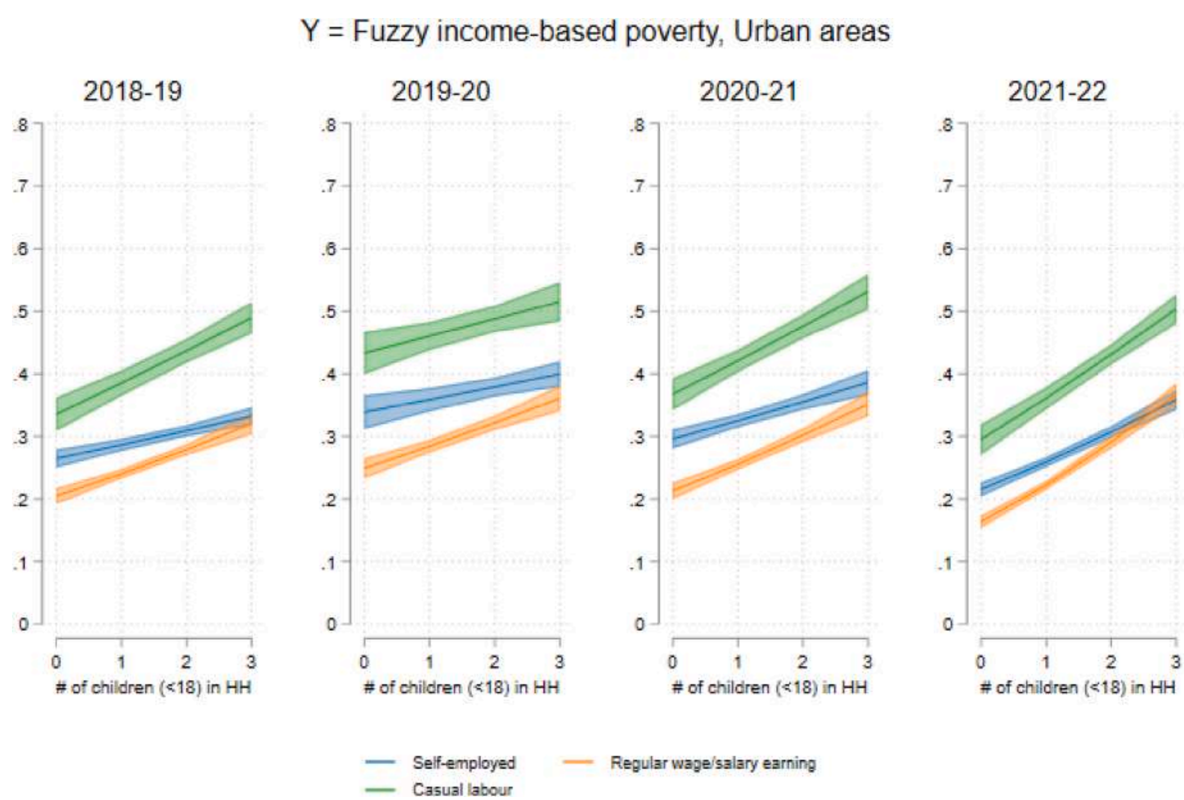

Fig. 8. Interaction between the number of children and HH labour characteristics, predictive margins, Urban areas
Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

rural areas, the gap between two key self-employment categories – i.e., agriculture (in red) vs non-agriculture (in blue) - steadily diminishes. In the earlier period of 2018–19, the red curve exceeded the blue one, indicating a higher risk of poverty for households relying on agricultural self-employment. However, by 2021–22, these two curves overlap, reflecting a narrowing of the poverty risk gap. Women living in households where self-employment serves as the primary income source tend to exhibit lower poverty risks compared to those reliant on casual labour. In urban settings the presence of working-age women within households yields relatively stable patterns regarding poverty risks, showing an interesting contrast with the shifts observed in the rural settings.

b) Fuzzy income-based poverty

The results for labour income poverty show a slightly different scenario than consumption-based poverty. Figs. 7 and 8 present the interactions between the household labour characteristics and the number of children in the household for rural and urban areas. For the former, a distinct pattern emerges for casual labour with three children. Their association with poverty increased in 2019–20, remained higher in the subsequent year, and reverted to pre-pandemic levels in the last period. Conversely in urban areas, as reported in Fig. 8, there is a temporary increase in the association with poverty observed among households without children and for those predominantly engaged in self-employment and regular earners. Following the initial wave of the pandemic, these categories recovered their previous positions, while HH with three children continued to show an association equal to or higher than the initial period.

Figs. 9 and 10 show the outcomes of the interactions with the number of working-age women. In rural areas, we observe significant variations primarily in regular wage earners (in orange) and among the self-employed in non-agricultural sectors (in blue). Analysing the slope of the curve, it becomes apparent that in 2019–20, the gap between households without working-age women and those with three or more women had narrowed in comparison to the 2018-19 period. This phenomenon could be attributed to the adverse effects of lockdown-induced closures, exacerbating the conditions for households with a higher male presence, bringing them closer in economic terms to those with a greater female composition. Nevertheless, the gap began to widen once more in 2020-21 and continued to expand further in 2021–22.

Fig. 10 reveals that casual labour and self-employed experienced an increase in the pandemic initial period (2019-20). In the subsequent periods, all groups rebounded to pre-pandemic levels, except for casual labourers households with two or three children.

4.3. *The multiple potential headcount ratio*

This section presents the trends and regression outcomes for the poverty specification (Equation (5)) that uses as dependent variables the MCHCR and the IHCR. The aim here is to ascertain whether the key findings from the fuzzy poverty estimations (Tables 2 and 3) remain robust when employing an alternative specification, although we expect some differences because it is a different method of measuring poverty. Below, we briefly describe the main differences. Additionally, in Appendix C, we provide the graphical representations of the heterogenous effects between labour-related variables and the number of children or number of working-age women.

a) Multiple potential headcount ratio (MCHCR)

Fig. 11 depicts the trend of extreme poverty as measured by the consumption-based MCHCR. The solid and slashed lines represent the mean of the multiple potential poverty values, whereas the dotted lines above and below these lines represent the maximum and minimum values. The results trends for urban areas are similar to those from the fuzzy results (Fig. 1), in which poverty levels remain stable after the first shock. For rural areas, the recovery after the first shock is more

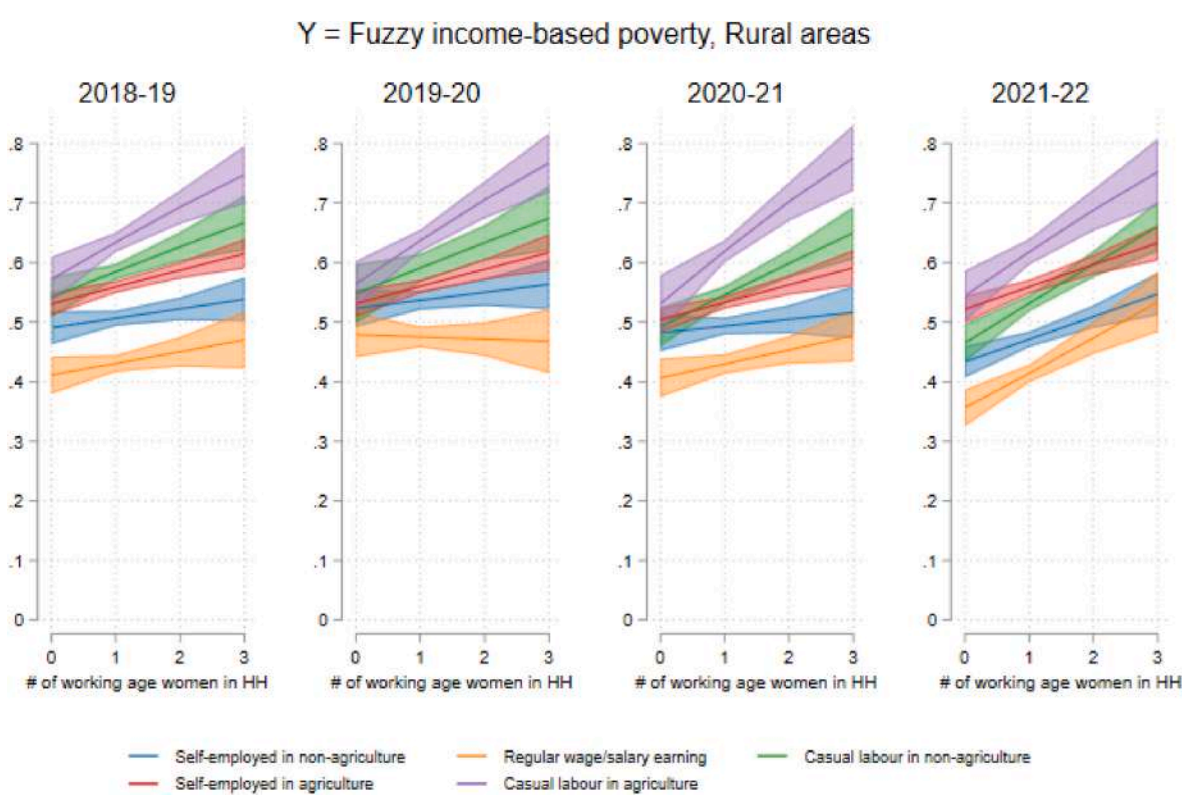

Fig. 9. Interaction between the number of working-age women and HH labour characteristics, predictive margins, Rural areas
Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

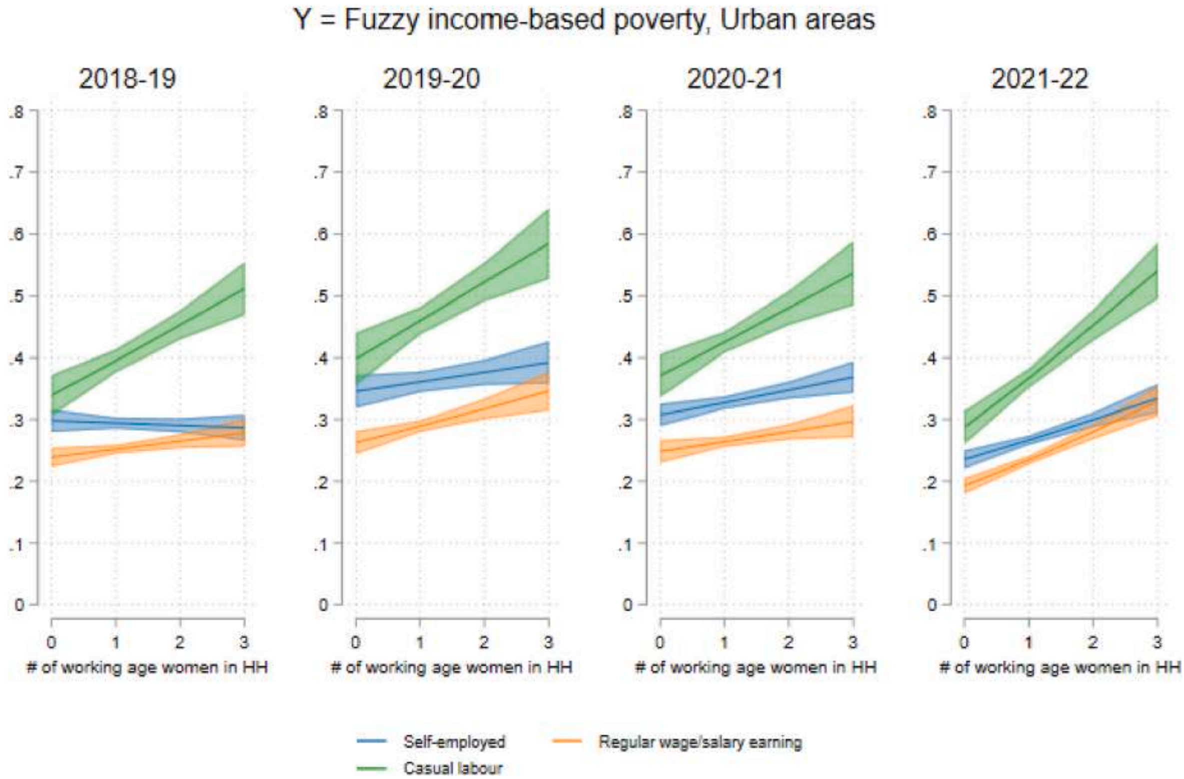

Fig. 10. Interaction between the number of working-age women and HH labour characteristics, predictive margins, Urban areas
Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

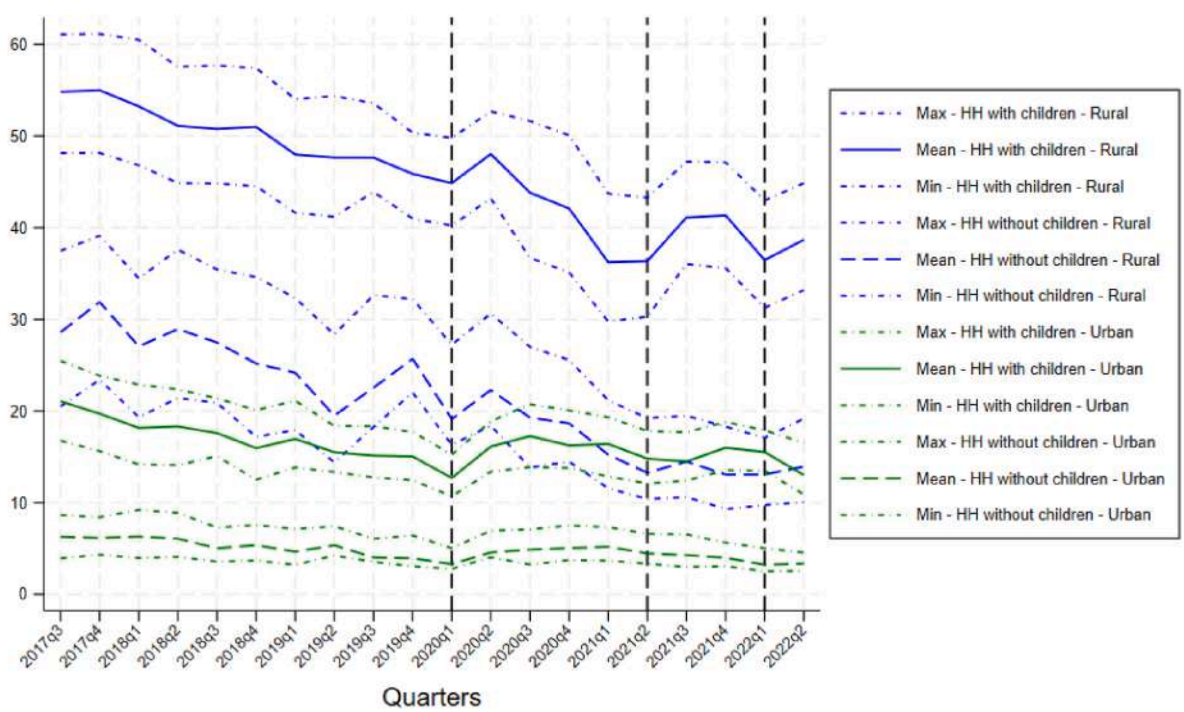

Fig. 11. Consumption-based MCHCR trends by quarter. Note: Outcomes are the percentage of extreme poverty. The three vertical dotted lines represent the main COVID-19 shocks when non-pharmaceutical interventions (NPI) took place in India.

pronounced than that from the fuzzy results, but, like the fuzzy specification, the recovery is interrupted after the second shock.

Table 4 presents the probit regression outcomes for the consumption-based MCHCR by area type. The patterns of change over time closely resemble those from the fractional regression presented in Table 2. However, the certainty of these time-related differences is less clear, owing to the introduction of variability from the multiple imputation process.

The outcomes confirm that households with children and families with a larger number of members are those with a higher probability of

Table 4
Probit regressions average marginal effects, consumption-based MCHCR.

Y= Consumption-based MCHCR	Rural				Urban			
Variables	2018–19	2019–20	2020–21	2021–22	2018–19	2019–20	2020–21	2021–22
# of working-age men (16–59)	0.042[a]	0.045[a]	0.053[a]	0.046[a]	0.015[a]	0.018[a]	**0.022**[a]	0.017[a]
	(0.006)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
# of working-age women (16–59)	0.031[a]	0.039[a]	0.039[a]	0.041[a]	0.017[a]	0.021[a]	**0.030**[a]	0.023[a]
	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
# of elderly (>59)	0.048[a]	0.041[a]	0.049[a]	0.049[a]	0.017[a]	0.024[a]	**0.028**[a]	0.023[a]
	(0.009)	(0.008)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
# of child (0–5)	0.103[a]	0.098[a]	0.105[a]	0.102[a]	0.046[a]	0.039[a]	0.052[a]	**0.038**[a]
	(0.005)	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
# of child (6–14)	0.098[a]	0.097[a]	0.094[a]	0.096[a]	0.039[a]	0.037[a]	**0.046**[a]	0.043[a]
	(0.004)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
# of child (15–17)	0.071[a]	0.057[a]	0.069[a]	0.071[a]	0.029[a]	0.027[a]	0.030[a]	0.026[a]
	(0.007)	(0.007)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Max education level in the HH	−0.017[a]	−0.017[a]	**−0.014**[a]	**−0.013**[a]	−0.012[a]	**−0.010**[a]	−0.010[a]	**−0.010**[a]
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share of employed in the HH	−0.117[a]	−0.097[a]	−0.131[a]	−0.157[a]	−0.090[a]	−0.082[a]	**−0.040**[a]	**−0.057**[a]
	(0.022)	(0.024)	(0.018)	(0.019)	(0.014)	(0.014)	(0.013)	(0.012)
Family composition (base = One-adult household)								
Couples	0.010	0.039[c]	0.026[c]	0.016	−0.022	−0.002	0.000	−0.003
	(0.024)	(0.021)	(0.014)	(0.016)	(0.014)	(0.011)	(0.011)	(0.009)
Joint family	0.062[b]	**0.108**[a]	0.098[a]	0.082[a]	0.012	0.018	0.029[b]	0.032[a]
	(0.025)	(0.022)	(0.017)	(0.018)	(0.015)	(0.012)	(0.012)	(0.010)
HH labour characteristic (base = regular wage earning)								
Self-employed in agriculture	0.102[a]	0.092[a]	**0.039**[a]	**0.019**[c]				
	(0.011)	(0.011)	(0.011)	(0.010)				
Self-employed in non-agriculture	0.045[a]	0.046[a]	0.040[a]	0.018	0.023[a]	0.030[a]	0.023[a]	0.014[a]
	(0.012)	(0.014)	(0.012)	(0.011)	(0.005)	(0.005)	(0.005)	(0.004)
Casual labour in agriculture	0.167[a]	0.156[a]	0.156[a]	0.136[a]				
	(0.015)	(0.018)	(0.015)	(0.014)				
Casual labour in non-agriculture	0.126[a]	0.115[a]	0.103[a]	0.114[a]	0.076[a]	0.071[a]	0.075[a]	0.069[a]
	(0.013)	(0.015)	(0.013)	(0.013)	(0.008)	(0.008)	(0.008)	(0.007)
Others	0.056[a]	0.059[a]	0.086	0.049[b]	0.008	0.005	0.011	0.005
	(0.020)	(0.020)	(0.018)	(0.021)	(0.012)	(0.011)	(0.009)	(0.010)
HH main occupation (base = High skill jobs)								
Low skill	0.084[a]	0.072[a]	0.075[a]	0.058[a]	0.046[a]	**0.030**[a]	0.035[a]	**0.024**[a]
	(0.011)	(0.014)	(0.011)	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)
Social group controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55,739	55,222	55,375	55,844	45,473	44,930	44,862	45,631

Notes: Linearized standard errors in brackets (taking account of the survey design and following Rubins' rule). Coefficients in bold are statistically significantly different from their corresponding 2018–19 values at $p < 0.1$ or lower.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

experiencing poverty. The main differences to the fuzzy outcomes are that, in urban areas, the subgroup "Couples" is not significantly different from one-adult households, and casual labour in urban areas does not show an increased association with poverty over time.

b) Income-based headcount ratio (IHCR)

Fig. 12 illustrates the trends of labour-income-based (extreme) poverty by quarters. Overall, the trends are similar compared to the fuzzy results (Fig. 2). However, the IHCR results have more prominent variations, especially in the quarter after the first shock (2020q2). In this specification, it becomes apparent that households in urban areas experienced a significant impact from the initial shock, with poverty levels more than doubling compared to pre-pandemic figures. Following this initial shock, all subgroups demonstrated a swift recovery, with subsequent oscillations and, except for HH in rural areas and without children, a slight downward path.

Table 5 presents the estimations for labour income poverty. The findings confirm those discussed in Table 3 for most variables. During the pandemic, households with higher number of working-age women experienced higher poverty, except in urban areas in the 2020-21 round. Compared to the initial period, the higher association with poverty for working-age women in 2021-22 is statistically significant, confirming their difficult to recover after the main pandemic shocks.

Households with children consistently show the highest and increasing probabilities of being poor (with exceptions noted for children between 15 and 17 years old in rural areas), but the marginal effects are not significant in urban areas in the year 2019–20. Other differences from the fuzzy outcomes indicate that joint families in rural areas are not statistically different from one-adult households during the pandemic. In addition, low-skill labour is not statistically different from high-skill labour during the initial period of the pandemic (2019-20) in rural areas and urban areas from 2018-19 until 2020-21.

5. Discussion and conclusion

In this study, we analyse changes in determinants of poverty during the pandemic and dig into which subgroups likely emerged as poor to shed light on the vulnerability and recovery capacity of different subgroups, which are crucial aspects to guide policy responses to meet the SDGs.

In particular, considering the statistical gap in India, we employed a fuzzy-set methodology and a multiple imputation method to reduce the limitations of the PLFS data for measuring poverty. Our analysis covered both consumption- and income-based poverty metrics, offering two perspectives that revealed diverse insights. These differences underscore

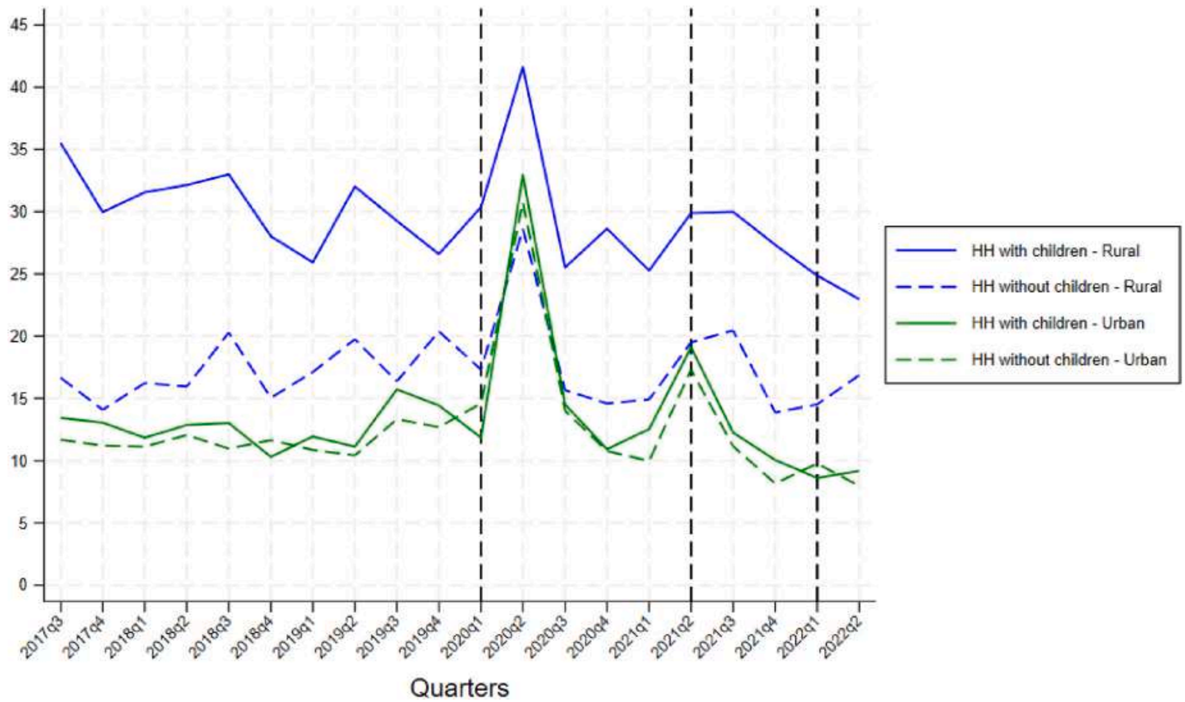

Fig. 12. IHCR trends by quarter. Note: Outcomes are the percentage of extreme poverty. The three vertical dotted lines represent the main COVID-19 shocks when non-pharmaceutical interventions (NPI) took place in India. The sample is restricted to households that have at least one person in the labour force.

the need to adopt a multi-faceted approach to poverty analysis, particularly when confronted with data limitations.

Overall, both sets of results highlight converging evidence in the association between household characteristics and the experience of poverty, albeit with some variations in focus. An important limitation of this study is that while the findings highlight the presence of significant correlations, they do not necessarily shed light on the direct cause-and-effect relationships between the control variables and poverty.

In terms of consumption-based poverty, it appears that the new categories of people falling into poverty are likely to be individuals living in larger households. This association increases over time and is notably influenced by factors such as the number of members (by generation) and the family composition, including couples and joint families. This finding suggests that, compared to small families, large ones may face additional challenges in terms of accumulating savings and implementing effective consumption-smoothing strategies. When examining HH-predominant labour characteristics, children living in households primarily engaged in casual labour in urban areas are highly at risk. Casual labour provides few opportunities for households to invest in developing skills and building assets, and unequal power relations with employers' limit households' capacities to improve their security or working conditions.

When looking at income-based poverty, there are two emerging categories: households with children and working-age women. When comparing the pre-pandemic and post-pandemic periods, it became apparent that all age groups of children experienced an increase in the association with poverty, and a noticeable gender disparity has become more pronounced over time. The number of working-age men was negatively associated with poverty, while the number of working-age women was positively associated with poverty and this positive association has intensified over time.

This gender gap reflects the persistent challenges faced by women in the Indian labour market, including issues of low job dynamism and job quality (see [29,30]). These factors all contribute to heightening the risk of women falling into poverty. The low proportion of women in the labour force often relies on precarious employment arrangements without adequate protection. Some women have joined the workforce in response to the pandemic-induced income loss within their households [30]. However, women typically enter the labour force under precarious informal employment conditions, with an insecure income source that often proves insufficient to compensate for the initial loss.

Joint families emerge as another group at particular risk, especially in rural areas. Notably, in urban settings, the association between joint families and income-based poverty is less significant when compared to one-adult households in most periods. This result suggests that a higher number of members can serve as a form of safety net as long as they are employed or receive social assistance, which is more likely to be the case in urban areas. In contrast to the analysis of consumption-based poverty, people falling into income-based poverty are also more likely to have jobs that require fewer skills. In the period under analysis, low-skilled workers faced a growing gap in terms of income compared to those with higher skills.

In both poverty specifications, regression interactions with labour-related variables indicate that in times of crisis vulnerability of women and children can also depend on the predominant type of employment. A higher number of children or working-age women in a household is consistently associated with higher poverty levels. This is more evident for those households primarily relying on casual labour, which, different from the other labour types, continued to be largely associated with poverty after the pandemic shocks.

In general, the alternative specification closely aligns with the fuzzy specification, reinforcing the key findings. There are differences in magnitudes and in a few coefficient significances, but the coefficient signs are almost always the same and the key findings still hold. Therefore, the pandemic has either perpetuated or exacerbated the economic precarity of historically vulnerable groups.

This paper helps identify individuals most at risk during the different phases of the pandemic. In terms of the policy implications one key area that requires policy attention is the enhancement of working conditions for women, especially those with dependent children. This involves improving their access to the labour market, creating a supportive work environment, safeguarding their rights, and establishing social safety nets to protect their children during crises.

For instance, on the supply side, it is essential to implement policies

Table 5
Probit regressions average marginal effects, labour income IHCR.

Y= Income-based IHCR	Rural				Urban			
Variables	2018–19	2019–20	2020–21	2021–22	2018–19	2019–20	2020–21	2021–22
# of working-age men (16–59)	−0.051[a]	**−0.013**	−0.039[a]	−0.030[a]	−0.030[a]	−0.020[b]	−0.032[a]	−0.018[a]
	(0.010)	(0.012)	(0.011)	(0.010)	(0.006)	(0.010)	(0.007)	(0.006)
# of working-age women (16–59)	0.018[b]	0.031[a]	0.033[a]	**0.052**[a]	−0.002	**0.015**[c]	−0.004	**0.022**[a]
	(0.009)	(0.011)	(0.010)	(0.009)	(0.005)	(0.008)	(0.006)	(0.004)
# of elderly (>59)	0.041[a]	0.048[a]	0.039[a]	0.039[a]	0.007	**0.029**[a]	0.007	**0.026**[a]
	(0.010)	(0.012)	(0.011)	(0.010)	(0.005)	(0.011)	(0.007)	(0.005)
# of child (0–5)	0.050[a]	**0.075**[a]	**0.076**[a]	**0.082**[a]	0.009[c]	0.003	0.020[a]	**0.026**[a]
	(0.007)	(0.010)	(0.008)	(0.007)	(0.005)	(0.007)	(0.006)	(0.004)
# of child (6–14)	0.048[a]	**0.083**[a]	**0.071**[a]	**0.086**[a]	0.007[b]	−0.000	0.011[b]	**0.028**[a]
	(0.006)	(0.007)	(0.006)	(0.006)	(0.003)	(0.007)	(0.004)	(0.003)
# of child (15–17)	0.062[a]	0.059[a]	0.080[a]	0.061[a]	0.014[a]	**−0.003**	0.015[b]	0.024[a]
	(0.010)	(0.013)	(0.011)	(0.010)	(0.005)	(0.009)	(0.007)	(0.005)
Max education level in the HH	−0.007[a]	−0.005[b]	**−0.003**[b]	−0.006[a]	−0.005[a]	**−0.008**[a]	−0.008[a]	**−0.003**[a]
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share of employed in the HH	−0.279[a]	**−0.020**	**−0.054**	**0.118**[a]	−0.307[a]	−0.346[a]	−0.276[a]	**−0.002**
	(0.049)	(0.049)	(0.041)	(0.038)	(0.026)	(0.040)	(0.033)	(0.024)
Family composition (base = One-adult household)								
Couples	−0.150[a]	**−0.045**[c]	**−0.068**[a]	**−0.058**[a]	−0.213[a]	−0.198[a]	**−0.153**[a]	**−0.046**[a]
	(0.028)	(0.025)	(0.023)	(0.022)	(0.024)	(0.028)	(0.025)	(0.016)
Joint family	−0.060[c]	**0.039**	**0.039**	**0.046**	−0.175[a]	−0.172[a]	**−0.102**[a]	**−0.012**
	(0.032)	(0.032)	(0.030)	(0.028)	(0.026)	(0.032)	(0.029)	(0.018)
HH labour characteristic (base = regular wage earning)								
Self-employed in agriculture	0.112[a]	**0.070**[a]	**0.078**[a]	0.132[a]				
	(0.013)	(0.016)	(0.014)	(0.014)				
Self-employed in non-agriculture	0.023[c]	0.051[a]	0.030[c]	0.010	0.022[a]	**0.058**[a]	0.022[a]	0.013[a]
	(0.014)	(0.017)	(0.015)	(0.013)	(0.006)	(0.010)	(0.007)	(0.005)
Casual labour in agriculture	0.229[a]	0.180[a]	**0.175**[a]	0.227[a]				
	(0.020)	(0.024)	(0.022)	(0.023)				
Casual labour in non-agriculture	0.158[a]	0.150[a]	**0.114**[a]	**0.101**[a]	0.149[a]	**0.182**[a]	0.150[a]	0.123[a]
	(0.016)	(0.022)	(0.017)	(0.015)	(0.014)	(0.016)	(0.013)	(0.011)
Others	0.503[a]	0.504[a]	0.527[a]	**0.863**[a]	0.516[a]	0.479[a]	**0.586**[a]	**0.940**[a]
	(0.037)	(0.036)	(0.041)	(0.010)	(0.030)	(0.062)	(0.031)	(0.008)
HH main occupation (base = High skill jobs)								
Low skill	0.037[b]	0.023	0.040[a]	0.043[b]	0.004	−0.000	0.007	**0.021**[a]
	(0.015)	(0.019)	(0.015)	(0.017)	(0.008)	(0.010)	(0.007)	(0.005)
Social group controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,973	21,605	20,904	20,317	22,940	21,485	22,168	22,177

Notes: Linearized standard errors in brackets (taking account of the survey design). Coefficients in bold are statistically significantly different from their corresponding 2018–19 values at $p < 0.1$ or lower.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

to increase access to childcare and direct income support for families. On the demand side, measures should focus on job creation, reducing gender discrimination in the labour market, and enhancing women's access to traditionally male-dominated industries. Additionally, it is important to work towards improving the conditions of children living in households primarily led by women or where the predominant income comes from casual labour. These policies should prioritize universal measures while considering factors such as living in a rural or urban setting and ensure they do not increase the time burden of women.

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CRediT authorship contribution statement

Fernando Flores Tavares: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alessandro Carraro:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Conceptualization.

Declarations of interest

None.

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Appendix A. Limitations of the PLFS for measuring poverty

There are four main limitations of using the PLFS to estimate poverty. First, the available variable of consumption is the UMPCE, which is derived from a few questions rather than a detailed consumption questionnaire as in the Consumer Expenditure Survey. This variable has the purpose of classifying households into aggregated consumption classes, and not estimating household expenditure consumption [27]. As a result, poverty estimations using the UMPCE are only approximations and should be approached with caution.

Second, the method of collecting the UMPCE variable changed in the fourth round of the survey (July 2020–June 2021). Before the fourth round, the field staff collected data on three aggregated consumption categories (i.e., usual expenditure for household purposes, annual purchase of household durables, and imputed values of consumption from wages in kind, home-grown stock, and free collection) to build a single monthly variable. Beginning in the fourth round, the field staff started to collect data on five aggregated consumption categories (i.e., usual expenditure for household purposes excluding items like clothing and footwear, annual purchase of household durables, imputed values of consumption from wages in kind and free collection, imputed values of consumption from wages in kind, home-grown stock, and annual expenditure on items like clothing and footwear) to build five separated variables of household usual consumption expenditure from each of these aggregations. In addition, the consumption-related questions from the updated questionnaire have more details, giving more examples of items that compose the categories.

Due to the increased number of categories and additional details in the questionnaire, we expect that the new methodology will result in less underestimation of the usual consumer expenditure values compared to the prior methodology, especially for rural areas where imputed values of wages in kind and home-grown stock are more important than urban areas. Nevertheless, the categories remain similar, so we assume that the data collected by different rounds are still comparable to one another, although we maintain caution when analysing the outcomes.

Third, as Roy and van der Weide [12] argued, the UMPCE is subject to measurement error because of the high level of aggregation and the questionnaire design that requires a strong level of attention from respondents to accurately categorise expenses by component. These authors identified a large occurrence of consumption values around multiples of Rs. 1000, suggesting that this rounding error can significantly bias poverty estimations. We expanded their analysis by showing the share of values that are multiples of Rs. 500, Rs. 1000, and Rs. 2000 for all the PLFS rounds and all consumption variables that form the total household's usual consumption expenditure (see Table A1). We confirm that the large occurrence of rounding is present in all PLFS rounds.

Fourth, another potential source of problems with the data was the interruptions of data collection during the COVID-19 pandemic. The PLFS fieldwork was suspended for the first time in March 2020 until June 2020 and suspended again in April 2021 until June 2021. Both interruptions had spillover effects on the data collection for the subsequent quarters, and the delayed samples were collected retrospectively with reference to their original quarter[11].

Table A1

Percentage of reported household consumption expenditure values that are divisible by 500, 1000, and 2000 by PLFS rounds

	500					1000					2000				
	2017–18	2018–19	2019–20	2020–21	2021–22	2017–18	2018–19	2019–20	2020–21	2021–22	2017–18	2018–19	2019–20	2020–21	2021–22
Usual consumer expenditure	85.61	81.86	76.08			69.90	65.75	60.95			40.95	38.78	36.58		
Usual consumer expenditure for purposes out of goods and services				71.58	74.96				54.45	54.55				31.22	31.25
Expenditure on purchase of items like clothing, footwear etc.				81.03	81.28				66.74	60.16				42.32	36.24
Expenditure on purchase of durables like bedstead, tv, fridge etc.				80.29	78.22				68.94	62.23				51.58	45.27
Imputed value of usual consumption out of homegrown stock				71.08	71.02				61.29	61.15				53.07	54.97
Imputed value of usual consumption from wages in kind, free collection, gifts etc.				61.27	53.04				52.02	44.08				47.24	40.65

Note: Between 2017-18 and 2019-20 consumption expenditure was collected in only one variable. From 2020-21 onwards, consumption expenditure started to be collected in five variables.

Appendix B. Additional outcomes on occupation classification

a) Fuzzy consumption-based poverty

[11] For more details, refer to the website: https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1833855.

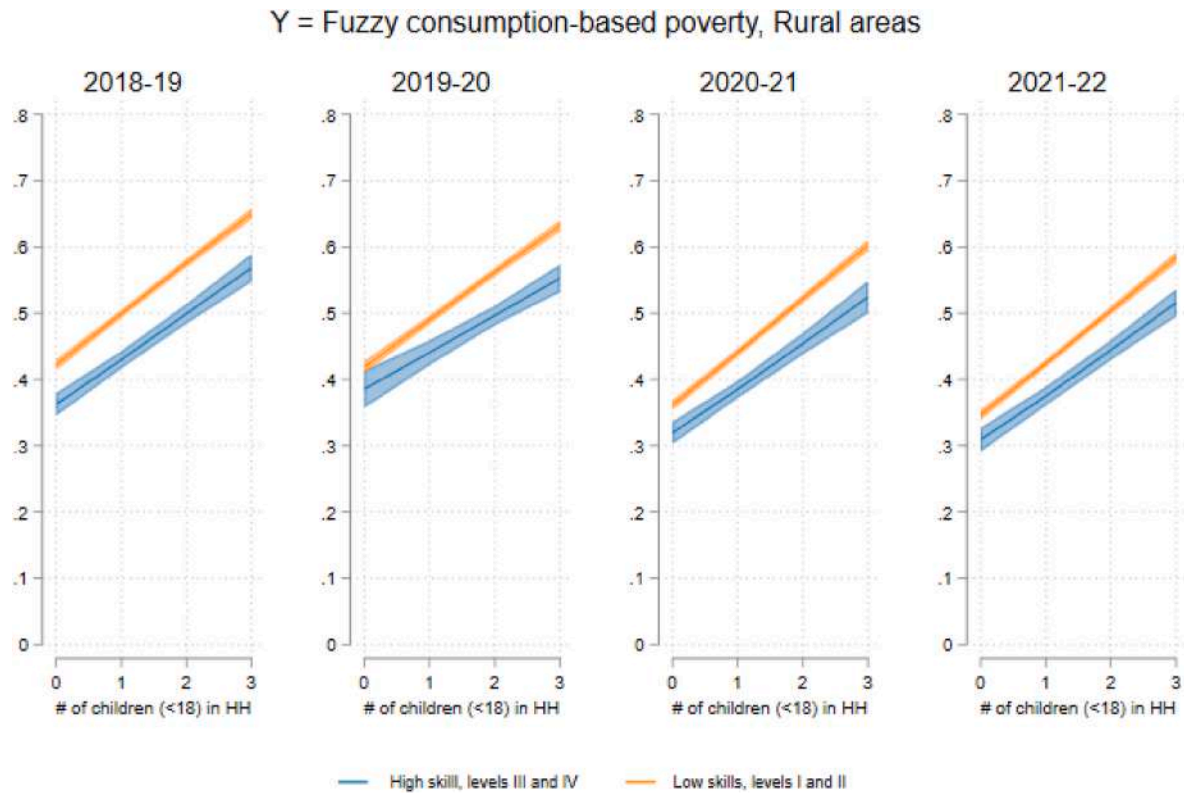

Fig. A1. Interaction between the number of children and HH main occupation type, predictive margins, Rural areas Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

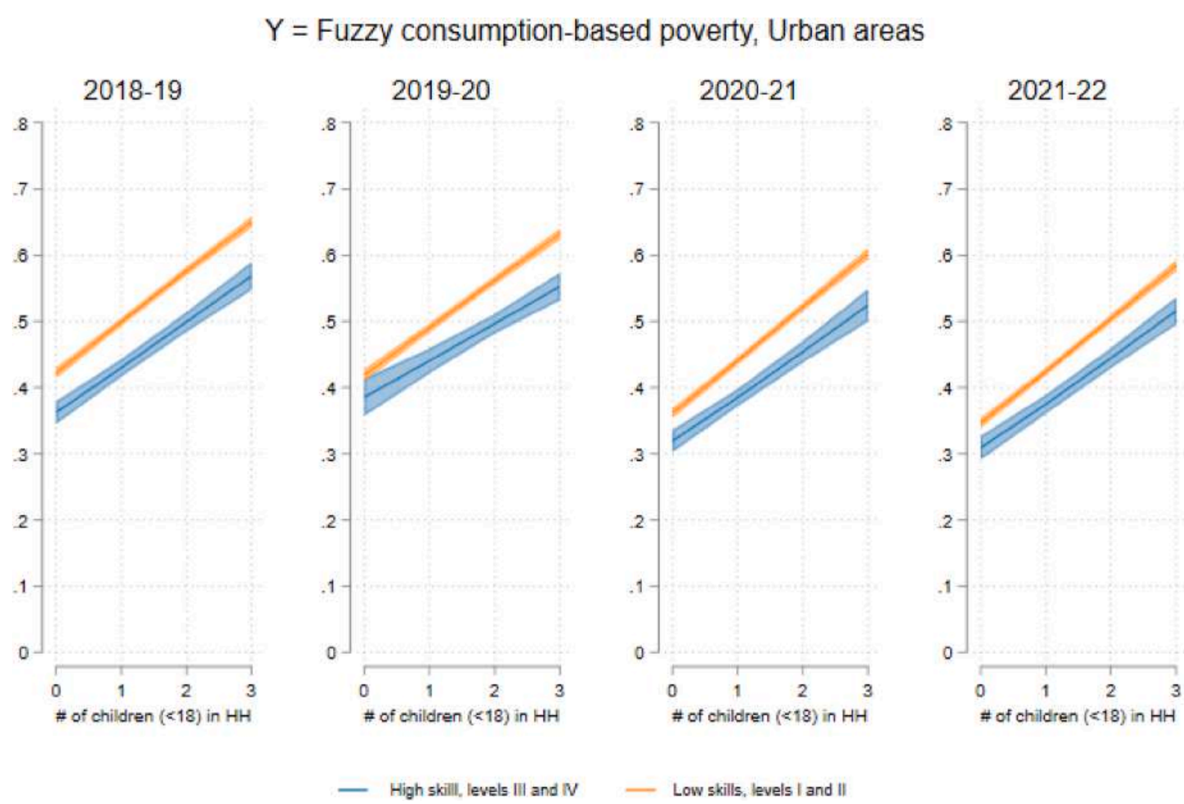

Fig. A2. Interaction between the number of children and HH main occupation type, predictive margins, Urban areas Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

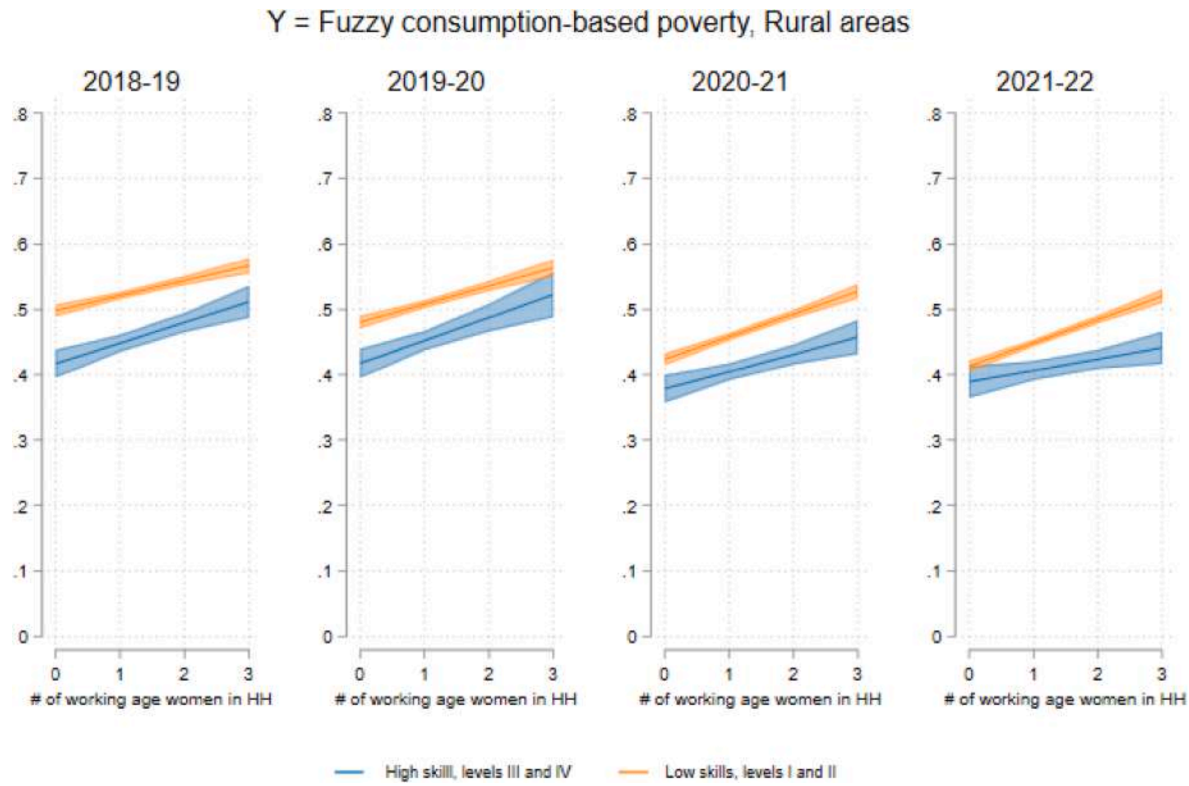

Fig. A3. Interaction between the number of working-age women and HH main occupation type, predictive margins, Rural areas Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

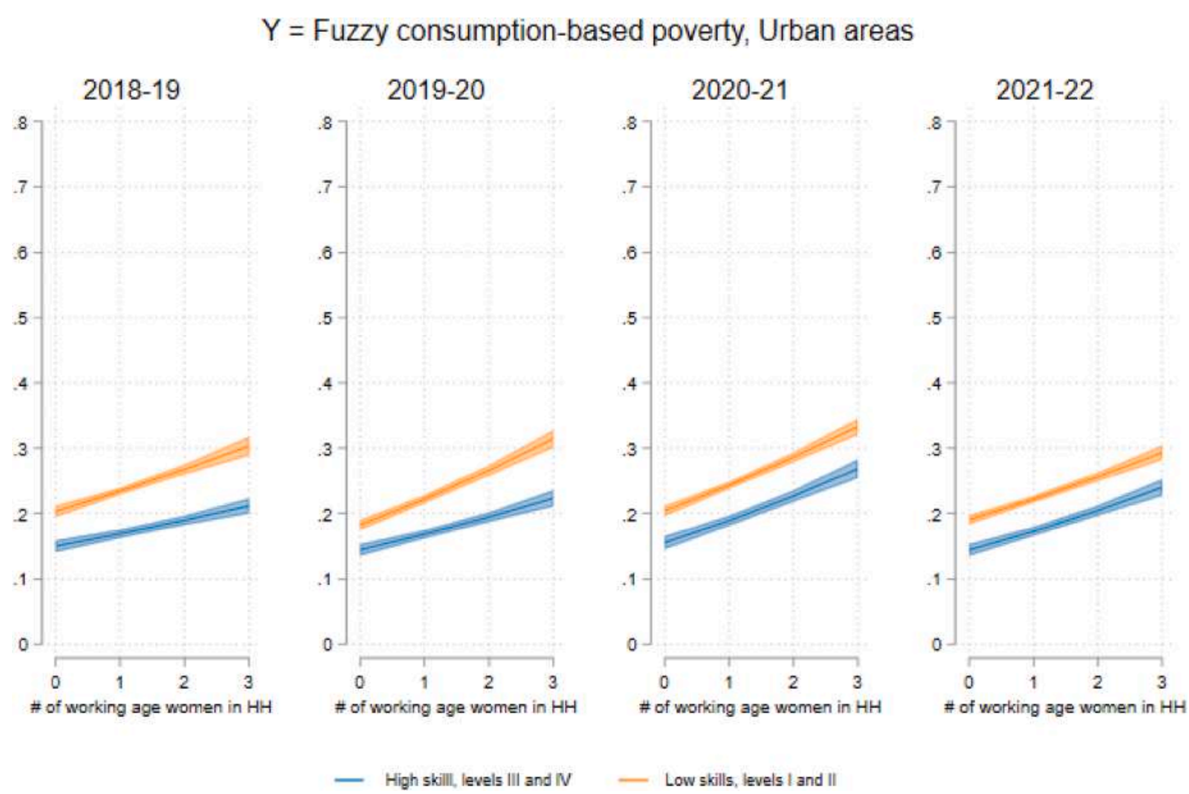

Fig. A4. Interaction between the number of working-age women and HH main occupation type, predictive margins, Urban areas Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

b) Fuzzy income poverty

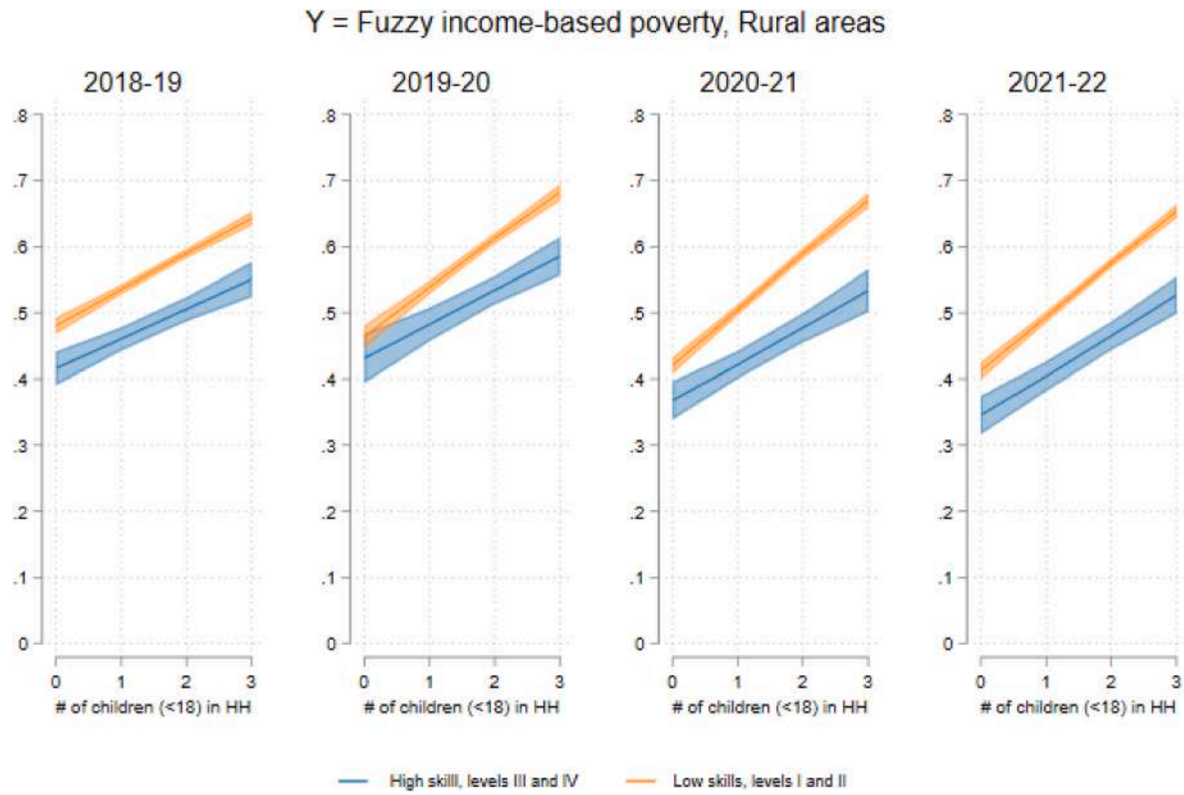

Fig. A5. Interaction between the number of children and HH main occupation type, predictive margins, Rural areas Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

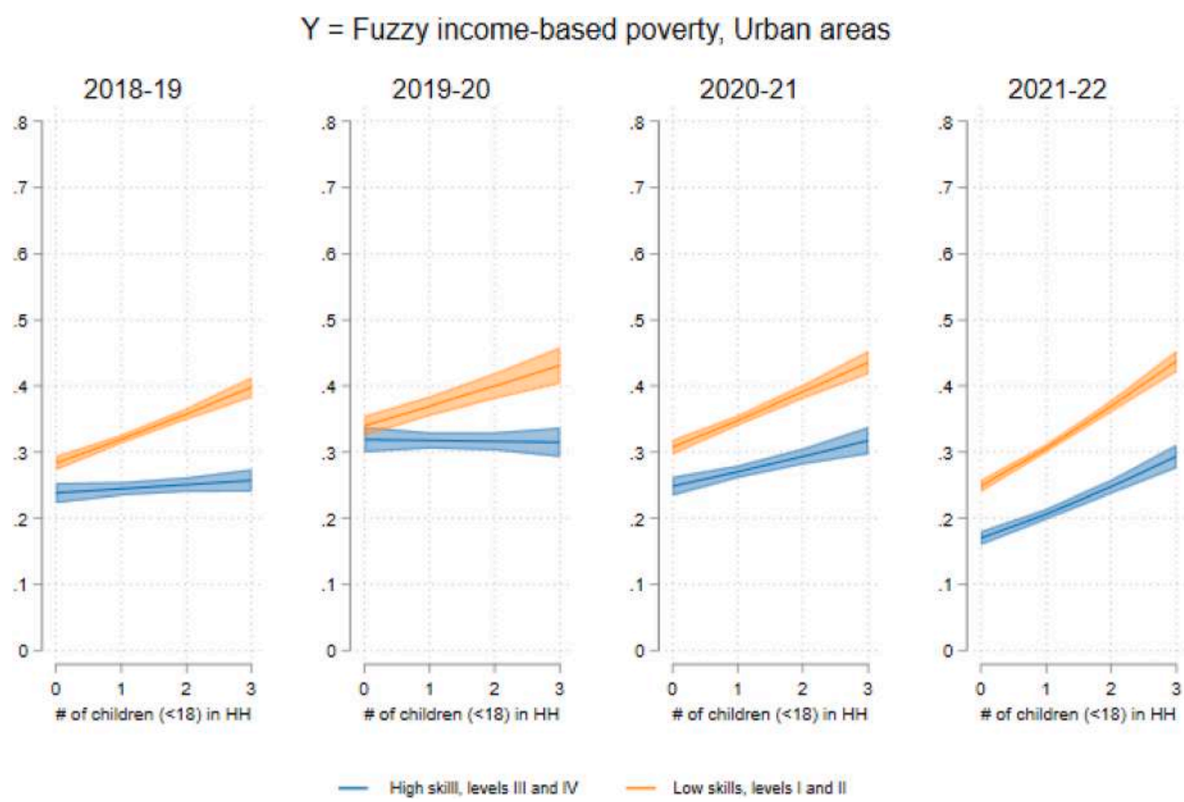

Fig. A6. Interaction between the number of children and HH main occupation type, predictive margins, Urban areas Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

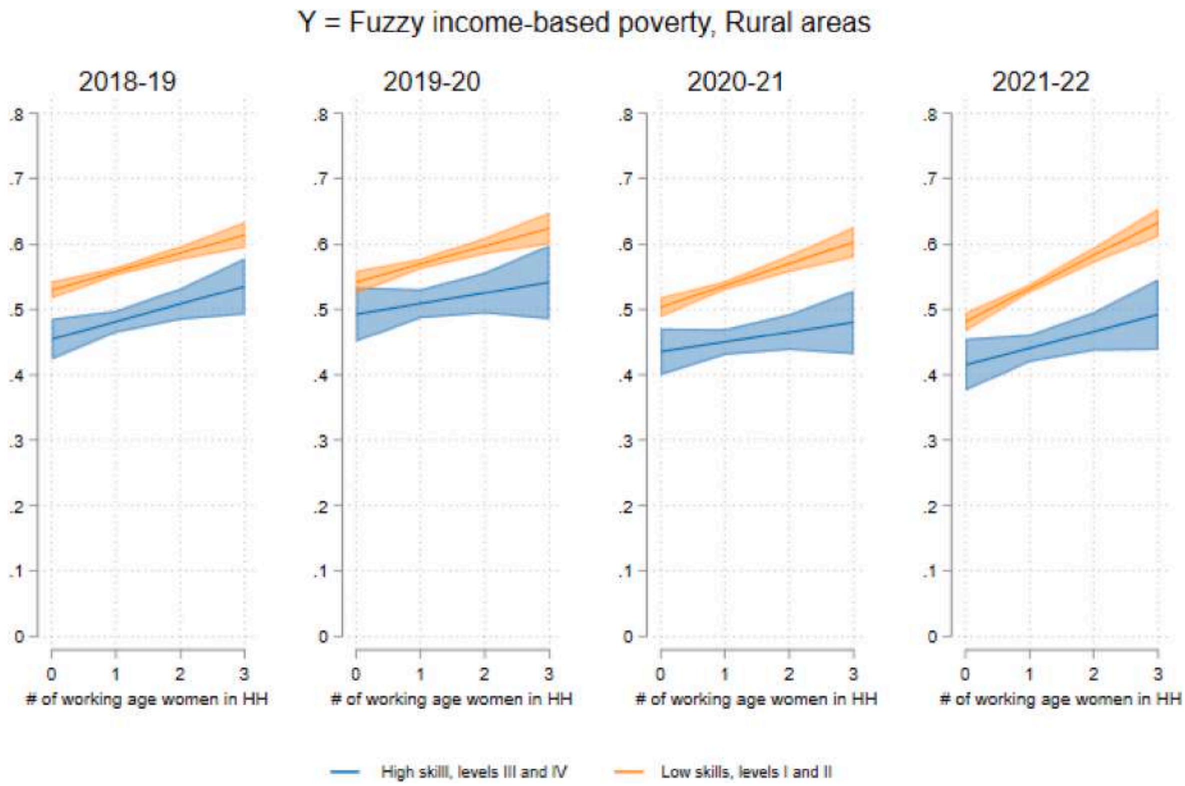

Fig. A7. Interaction between the number of working-age women and HH main occupation type, predictive margins, Rural areas Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

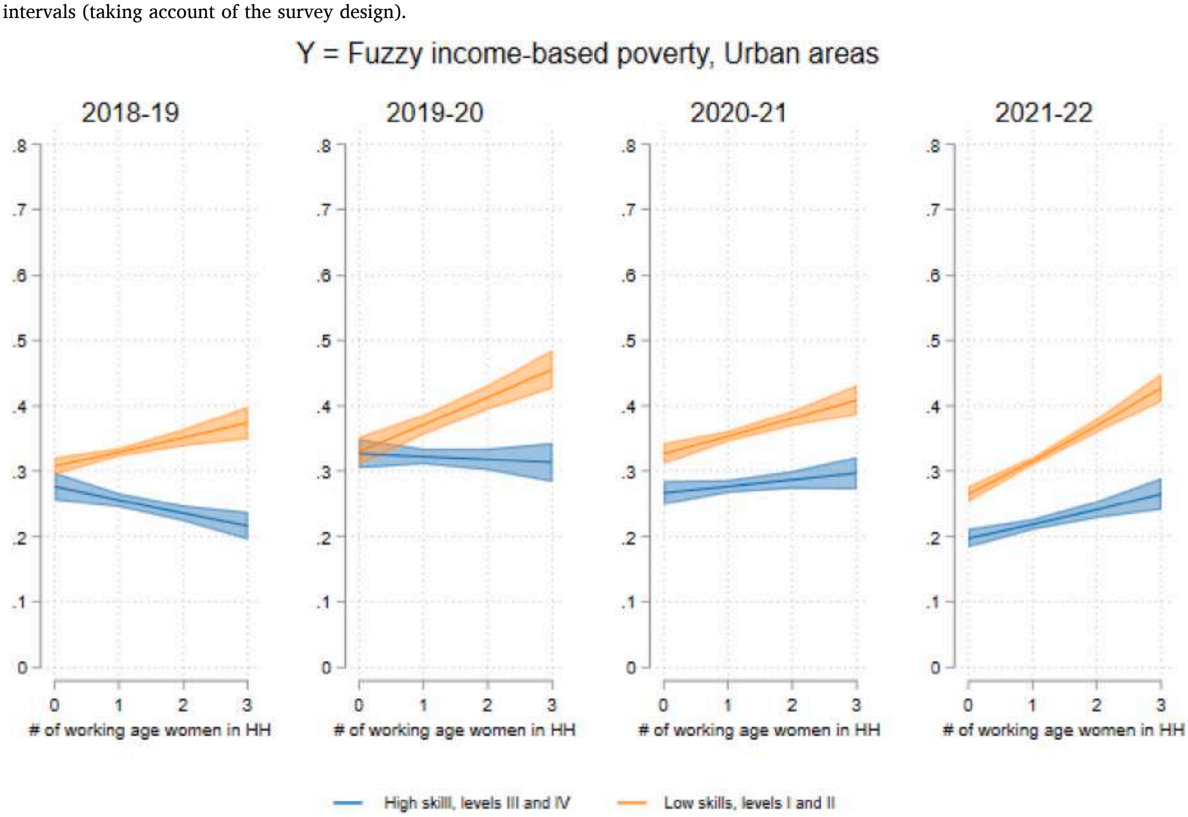

Fig. A8. Interaction between the number of working-age women and HH main occupation type, predictive margins, Urban areas Notes: Predictive margins with 95 % confidence intervals (taking account of the survey design).

Appendix C. Heterogeneous effects from the HCR specification

a) Multiple potential headcount ratio (MCHCR)

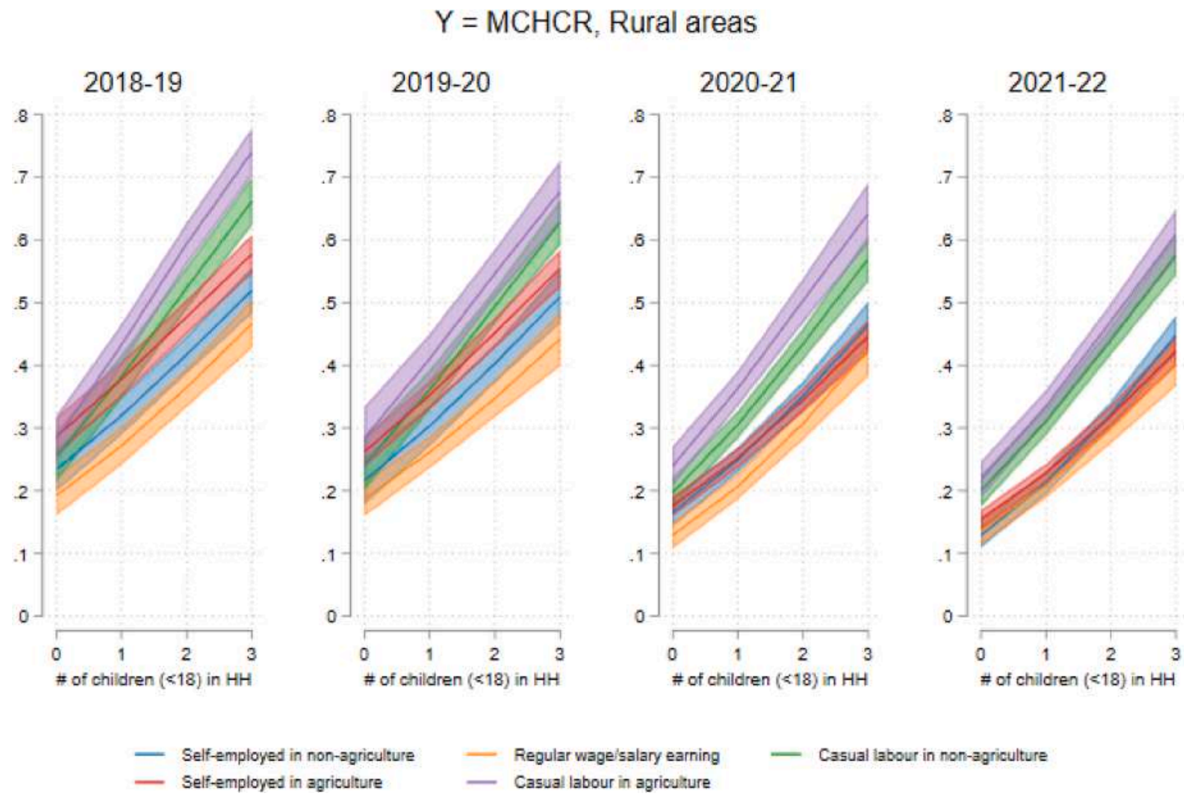

Fig. A9. Interaction between the number of children and HH labour characteristics, predicted probabilities, Rural areas Notes: Predictive margins with 95 % CI (taking account of the survey design and following Rubins' rule).

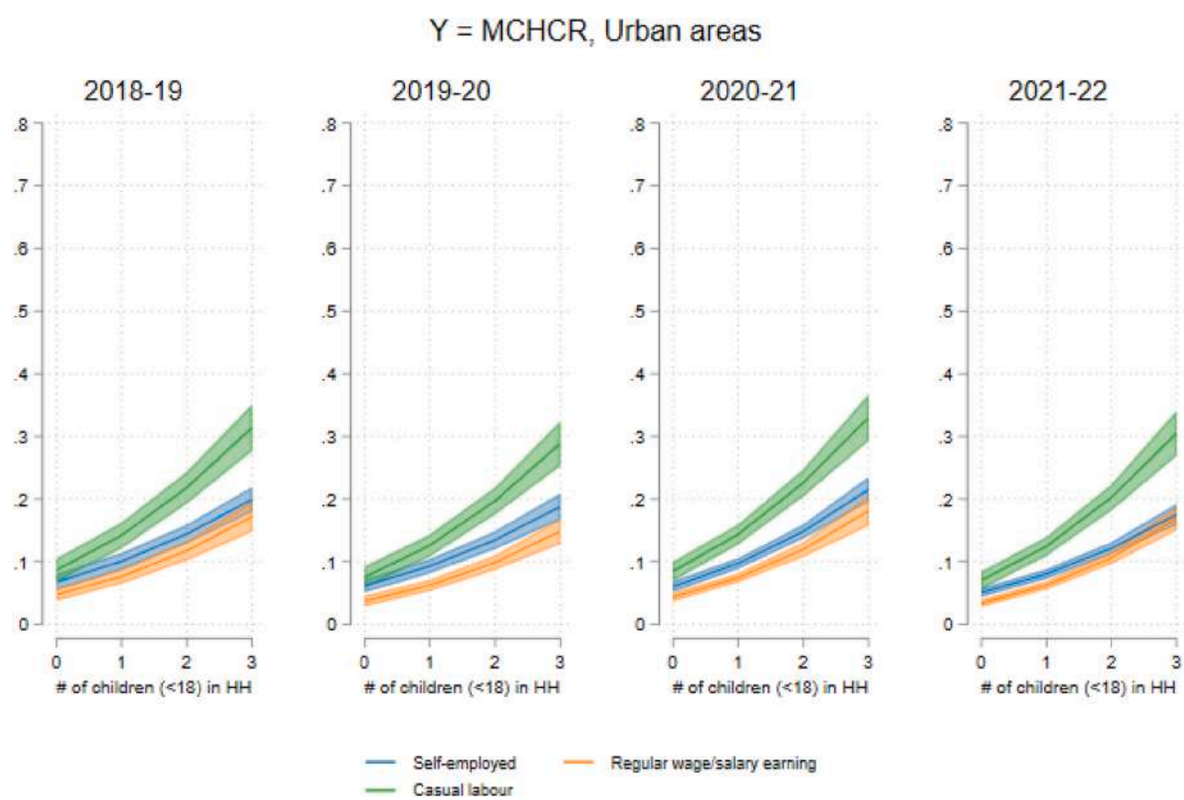

Fig. A10. Interaction between the number of children and HH labour characteristics, predicted probabilities, Urban areas Notes: Predictive margins with 95 % CI (taking account of the survey design and following Rubins' rule).

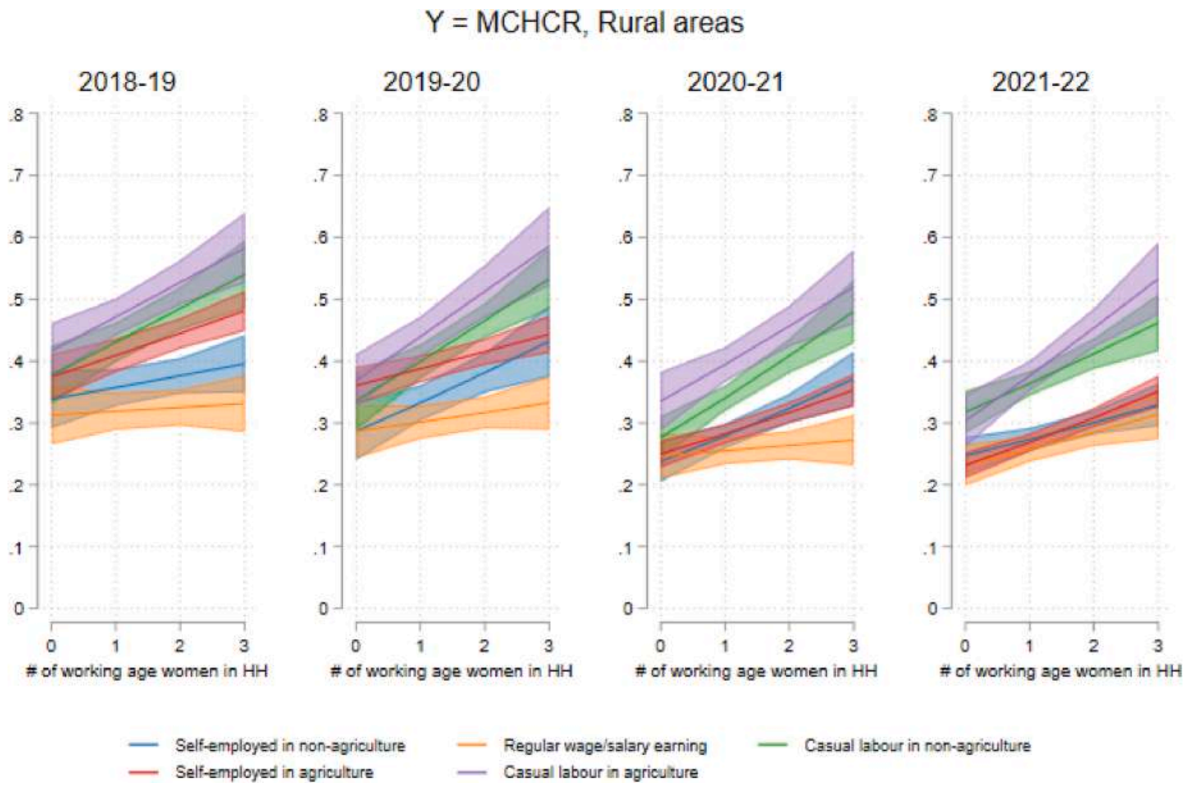

Fig. A11. Interaction between the number of working-age women and HH labour characteristics, predicted probabilities, Rural areas Notes: Predictive margins with 95 % CI (taking account of the survey design and following Rubins' rule).

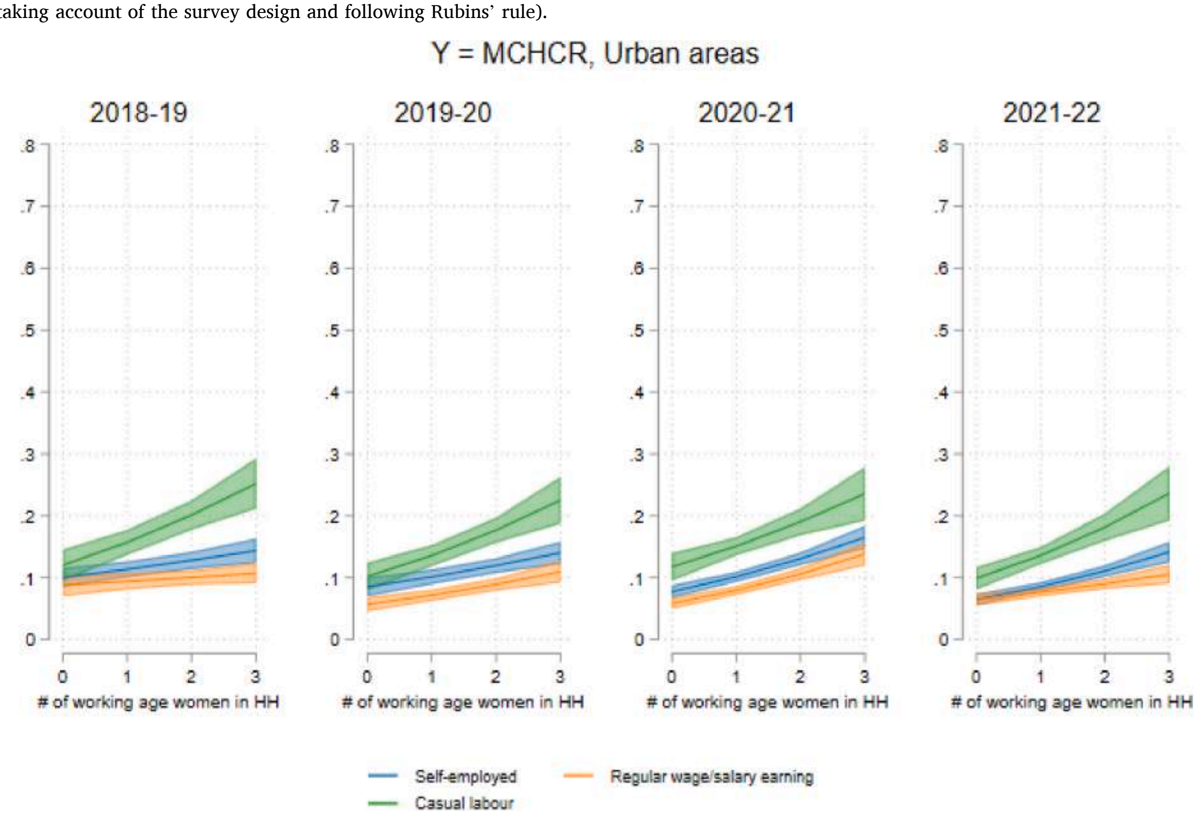

Fig. A12. Interaction between the number of working-age women and HH labour characteristics, predicted probabilities, Urban areas Notes: Predictive margins with 95 % CI (taking account of the survey design and following Rubins' rule).

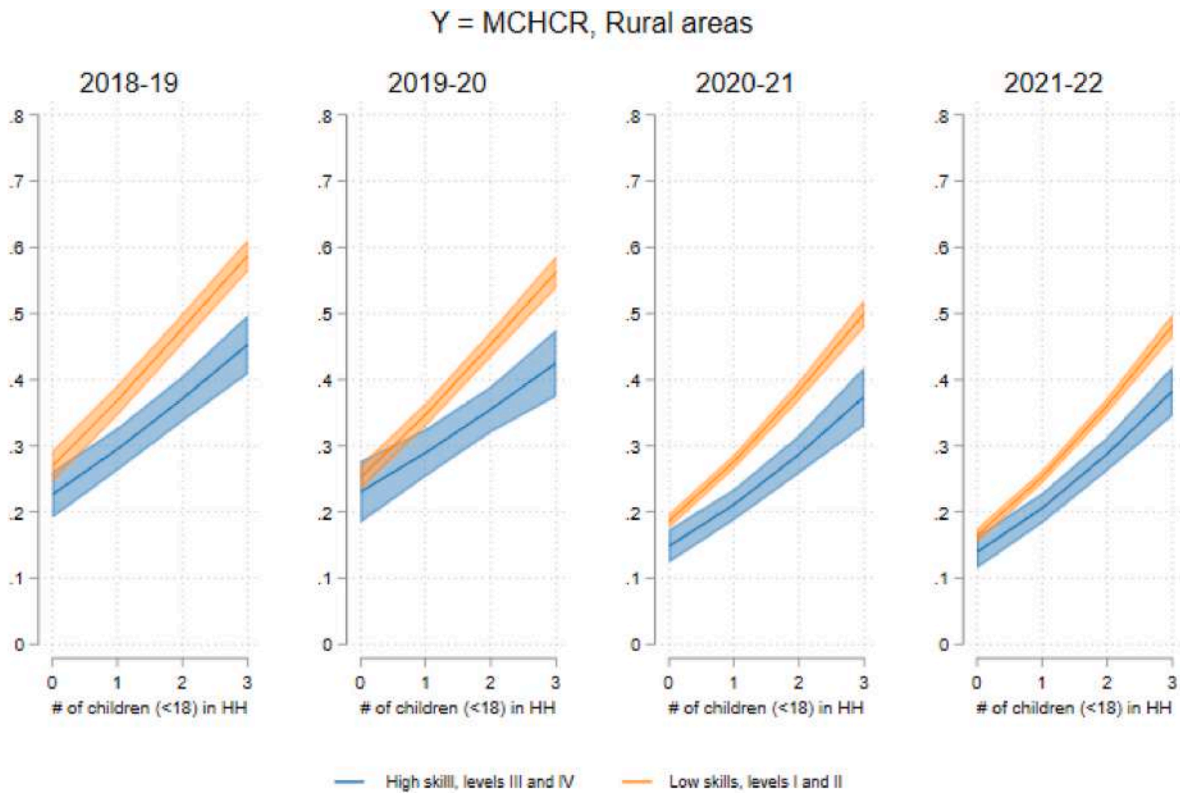

Fig. A13. Interaction between the number of children and HH main occupation type, predicted probabilities, Rural areas Notes: Predictive margins with 95 % CI (taking account of the survey design and following Rubins' rule).

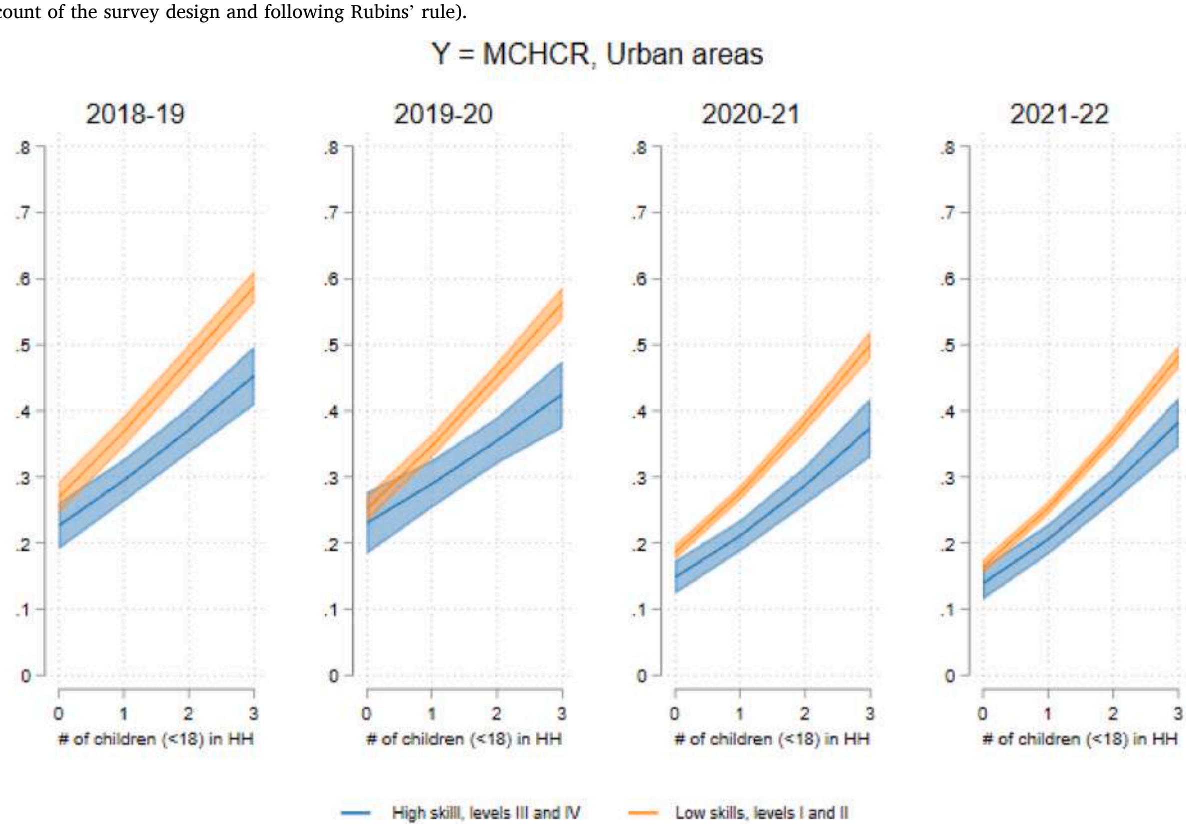

Fig. A14. Interaction between the number of children and HH main occupation type, predicted probabilities, Urban areas Notes: Predictive margins with 95 % CI (taking account of the survey design and following Rubins' rule).

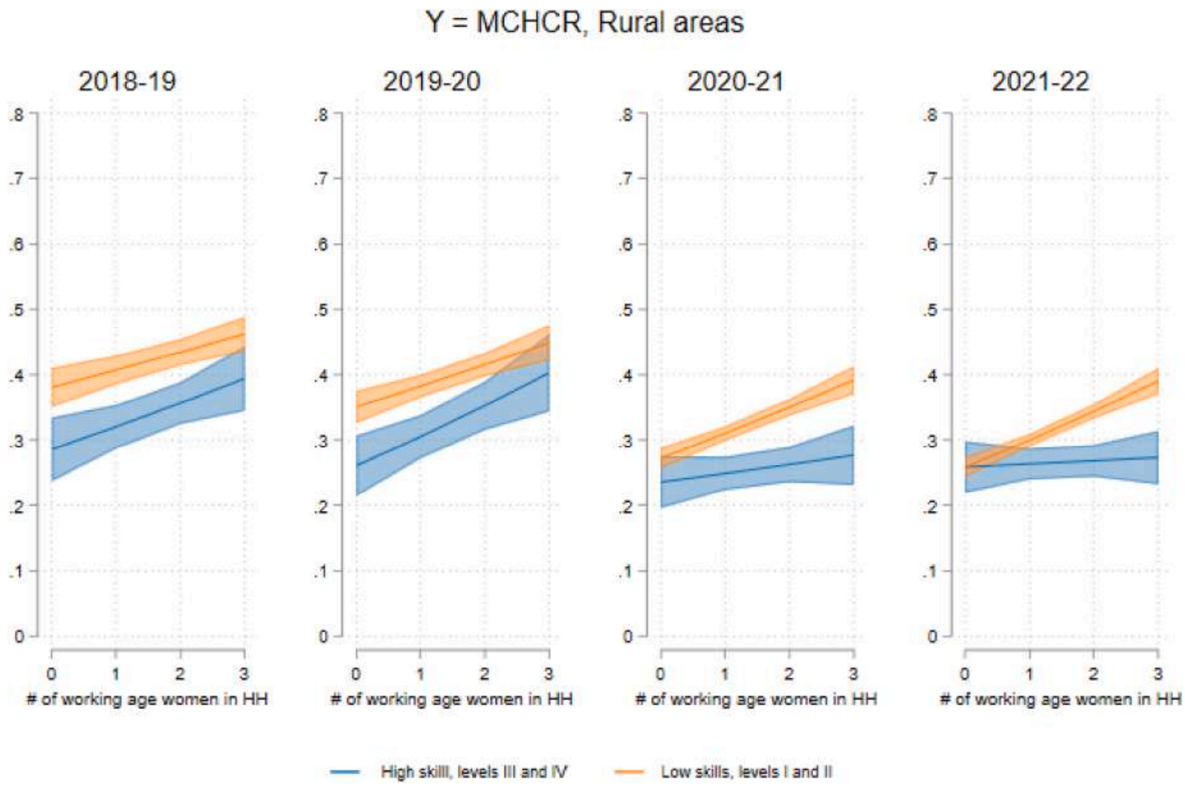

Fig. A15. Interaction between the number of working-age women and HH main occupation type, predicted probabilities, Rural areas Notes: Predictive margins with 95 % CI (taking account of the survey design and following Rubins' rule).

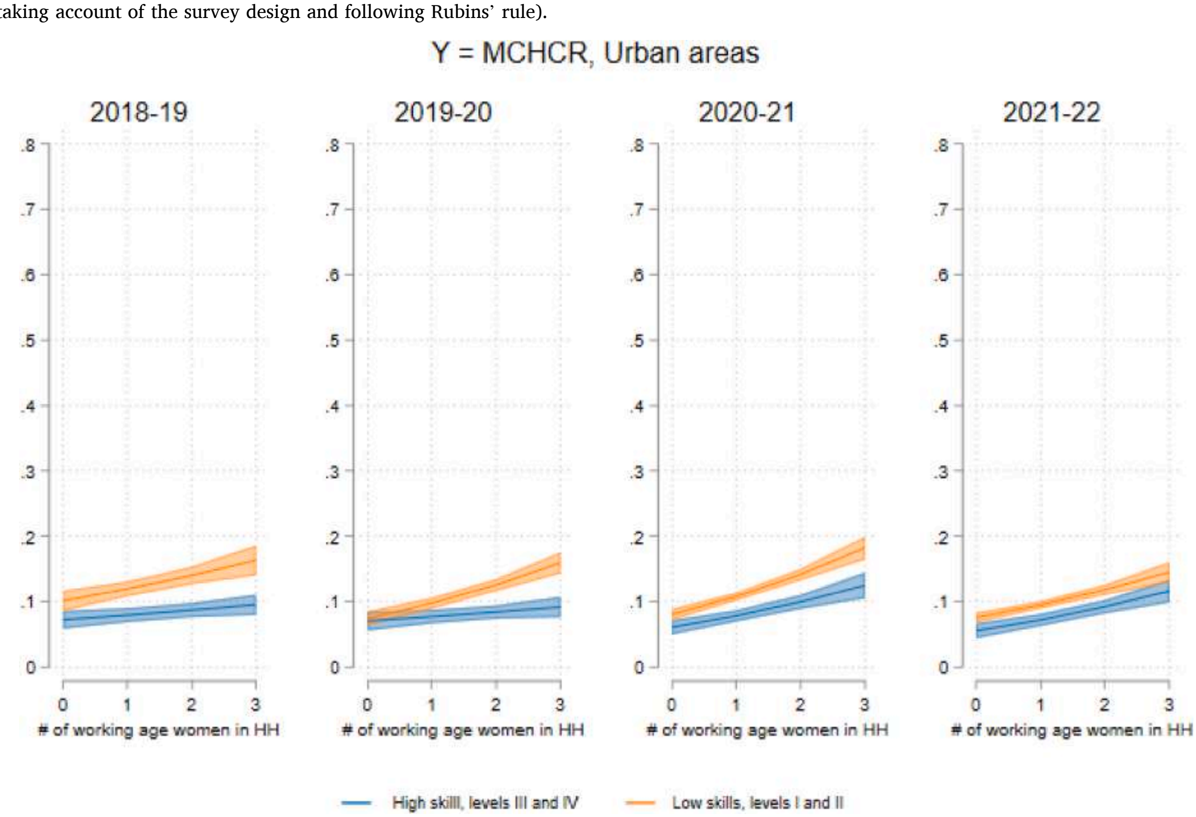

Fig. A16. Interaction between the number of working-age women and HH main occupation type, predicted probabilities, Urban areas Notes: Predictive margins with 95 % CI (taking account of the survey design and following Rubins' rule).

a) Income-based headcount ratio (IHCR)

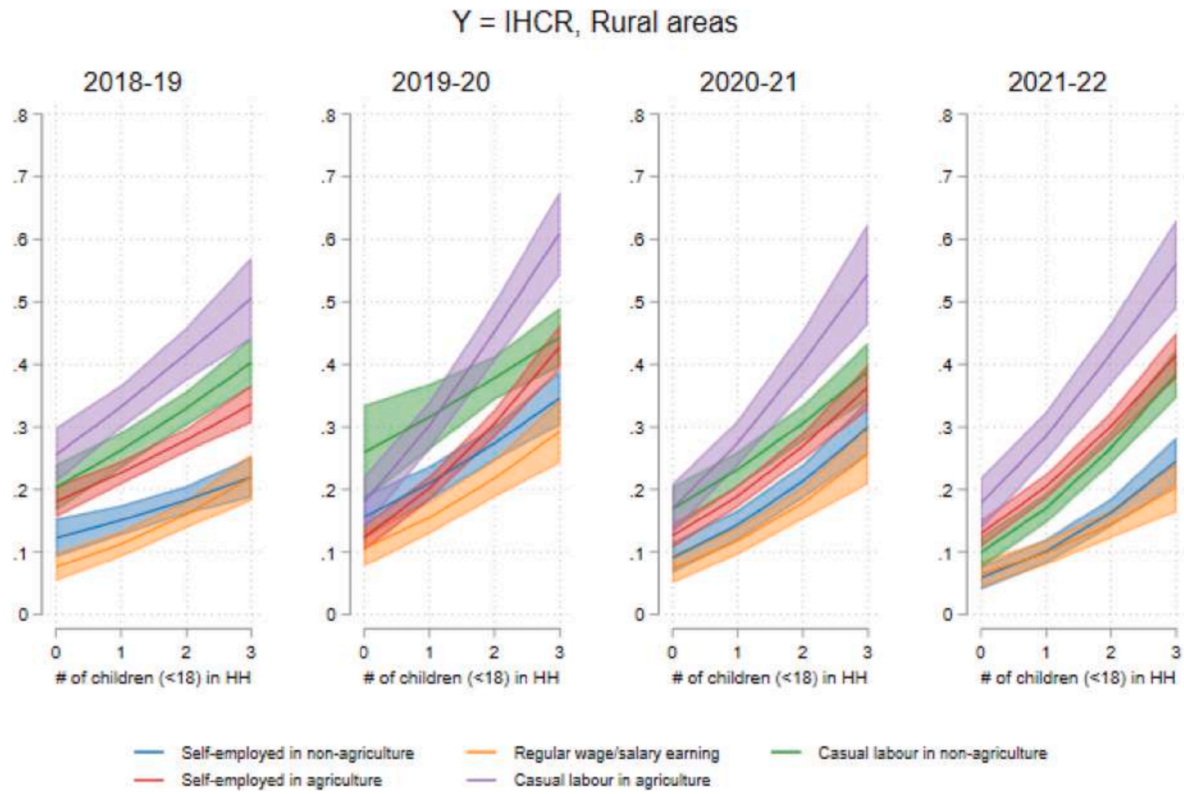

Fig. A17. Interaction between the number of children and HH labour characteristics, predicted probabilities, Rural areas Notes: Predictive margins with 95 % CI (taking account of the survey design).

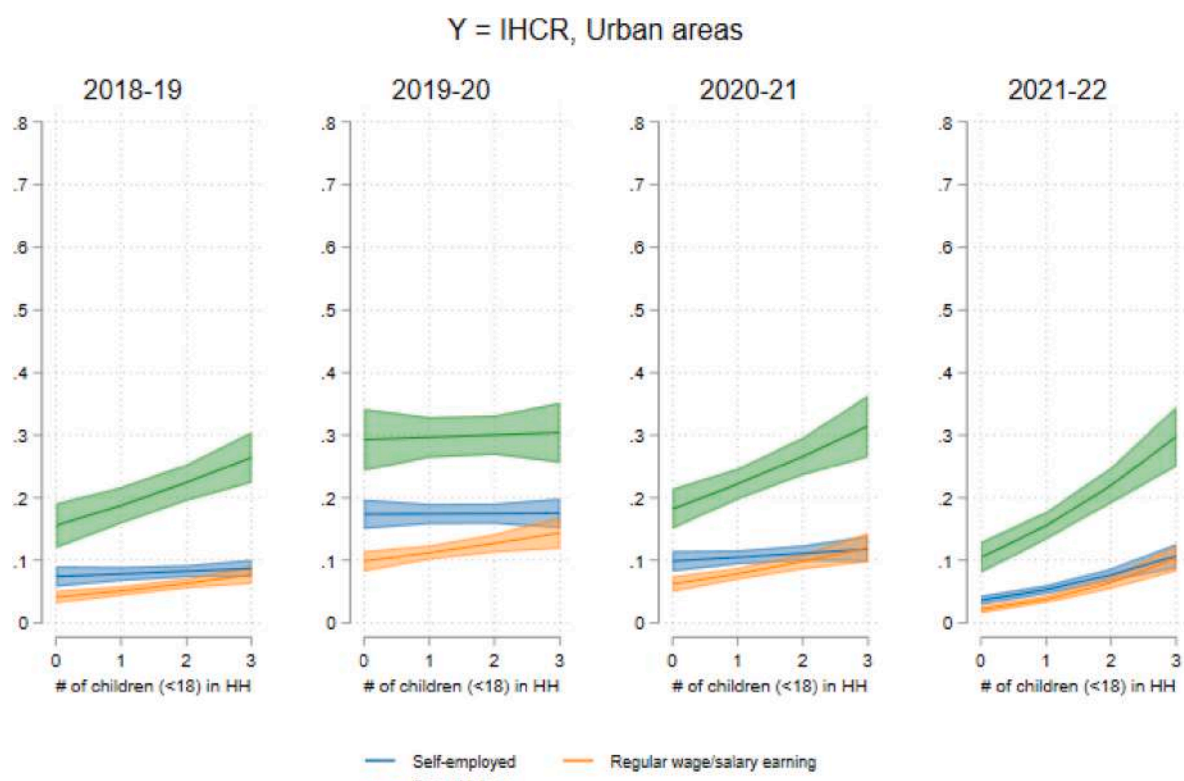

Fig. A18. Interaction between the number of children and HH labour characteristics, predicted probabilities, Urban areas Notes: Predictive margins with 95 % CI (taking account of the survey design).

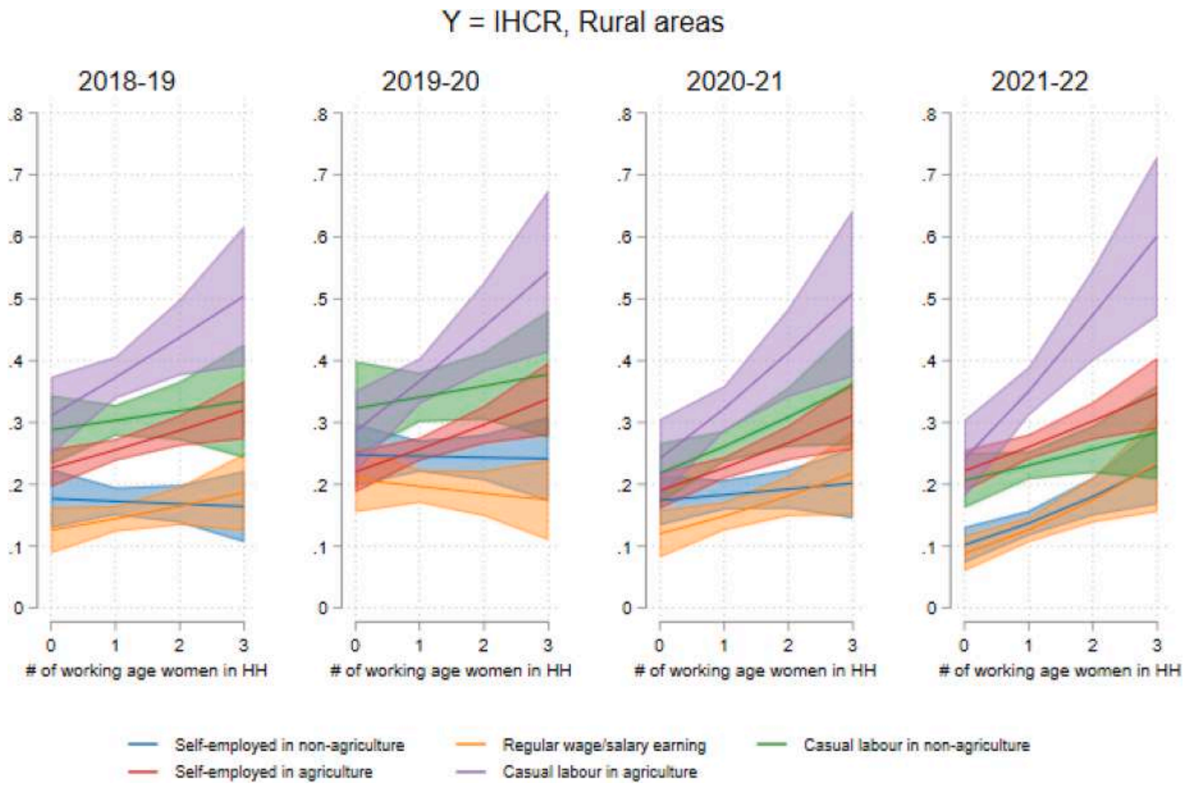

Fig. A19. Interaction between the number of working-age women and HH labour characteristics, predicted probabilities, Rural areas Notes: Predictive margins with 95 % CI (taking account of the survey design).

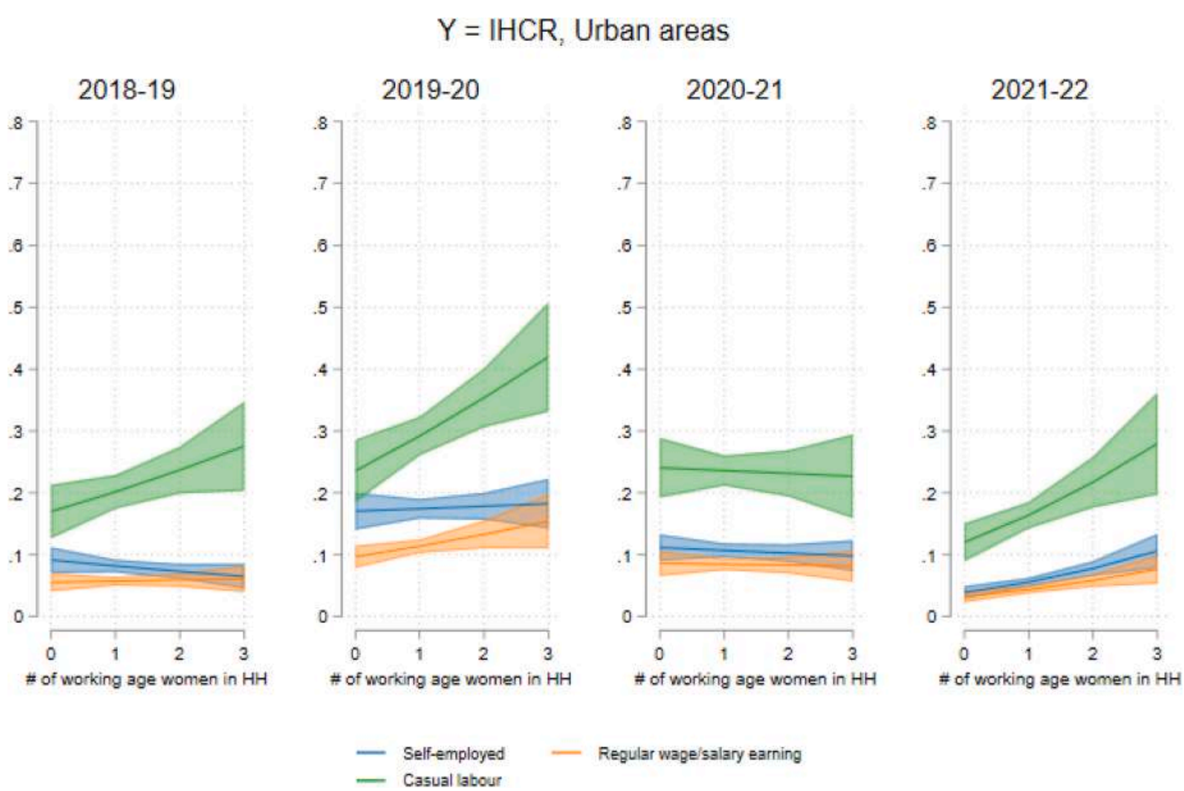

Fig. A20. Interaction between the number of working-age women and HH labour characteristics, predicted probabilities, Urban areas Notes: Predictive margins with 95 % CI (taking account of the survey design).

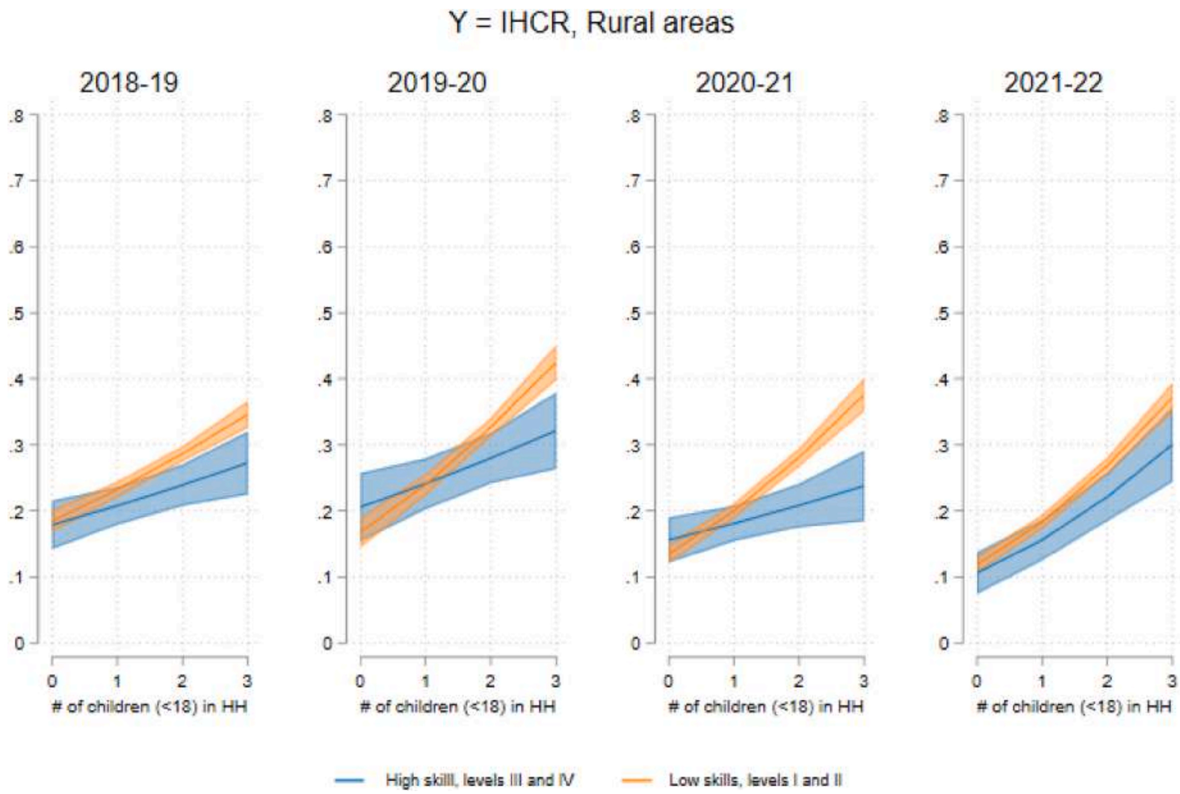

Fig. A21. Interaction between the number of children and HH main occupation type, predicted probabilities (Y = income poverty), Rural areas Notes: Predictive margins with 95 % CI (taking account of the survey design).

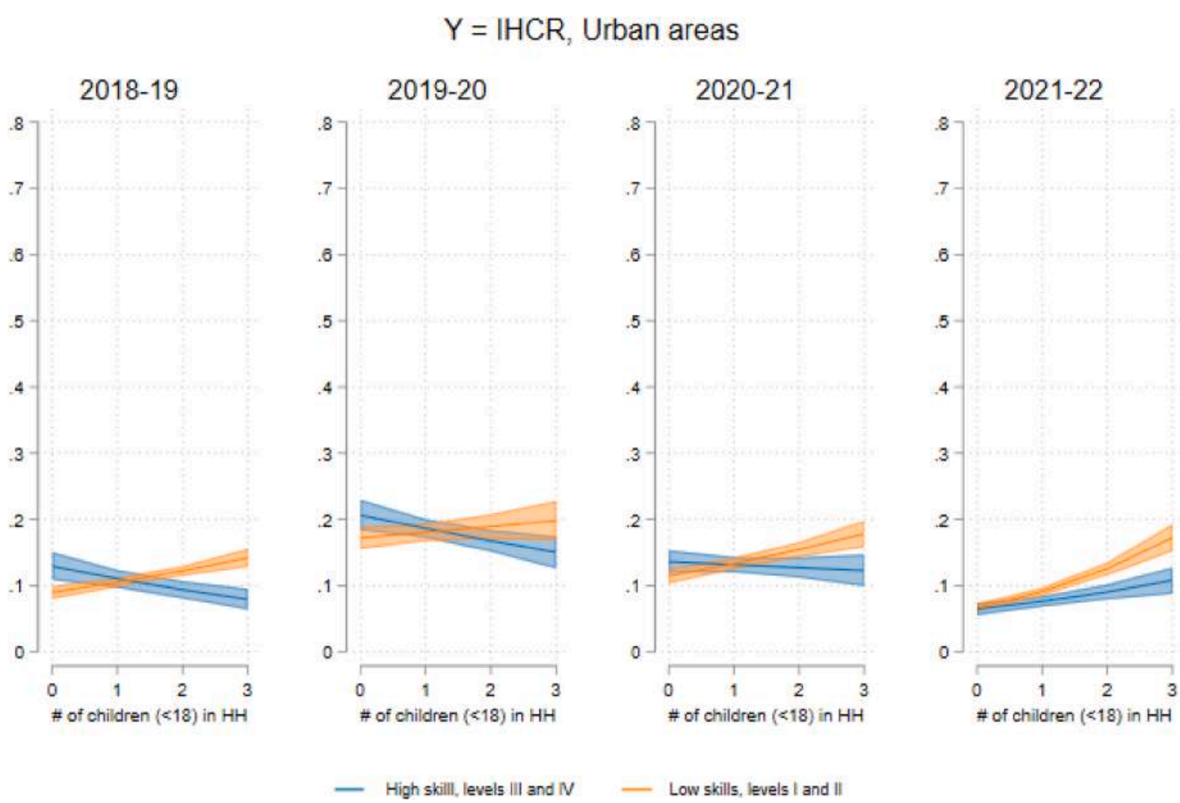

Fig. A22. Interaction between the number of children and HH main occupation type, predicted probabilities, Urban areas Notes: Predictive margins with 95 % CI (taking account of the survey design).

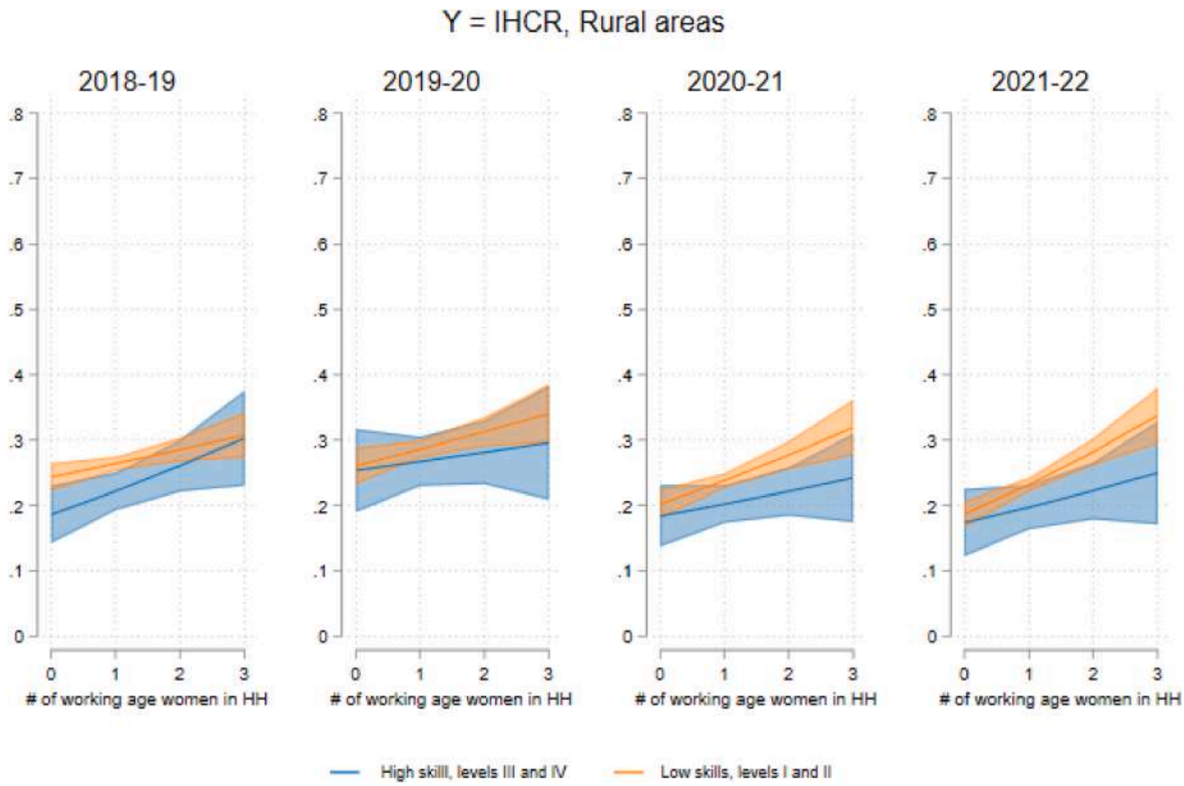

Fig. A23. Interaction between the number of working-age women and HH main occupation type, predicted probabilities, Rural areas Notes: Predictive margins with 95 % CI (taking account of the survey design).

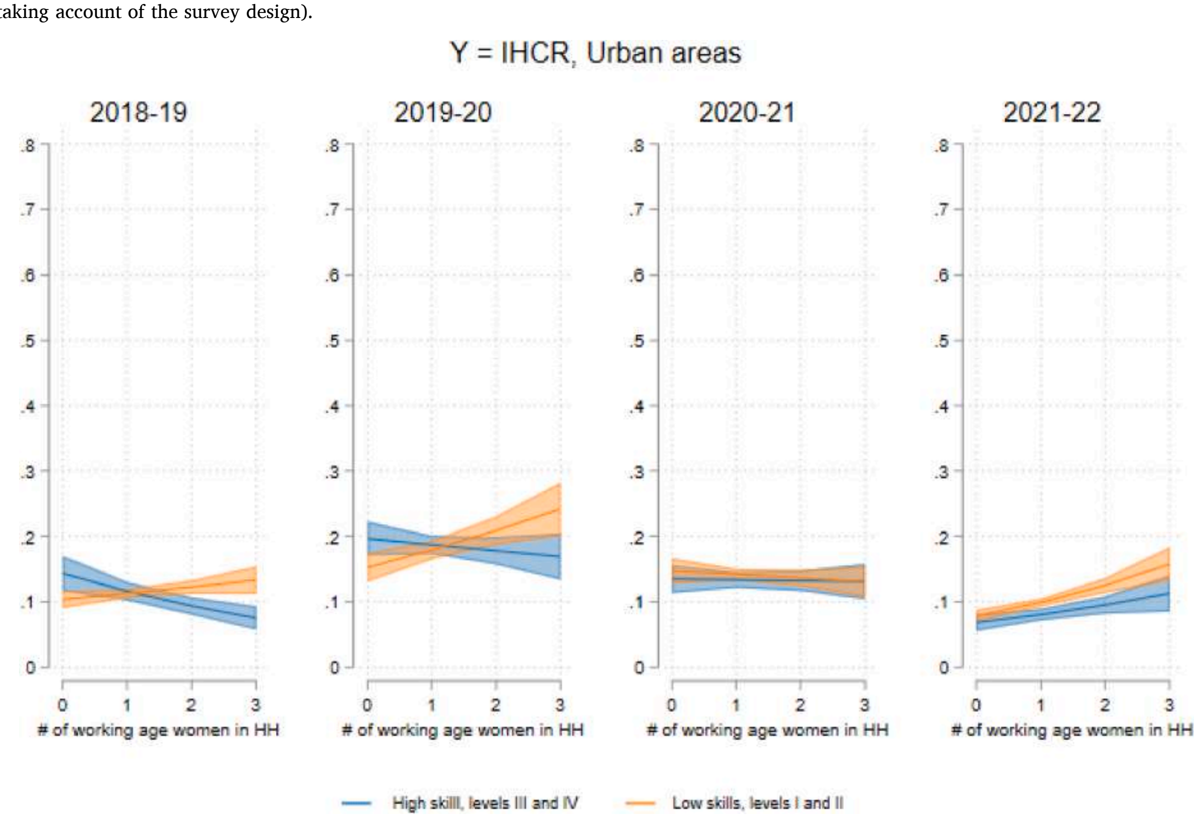

Fig. A24. Interaction between the number of working-age women and HH main occupation type, predicted probabilities, Urban areas Notes: Predictive margins with 95 % CI (taking account of the survey design).

Data availability

Data will be made available on request.

References

[1] UNICEF. Tracking the situation of children during COVID-19. Dashboard, UNICEF Data 2021. Retrieved from, https://data.unicef.org/resources/rapid-situation-tracking-covid-19-socioeconomic-impacts-data-viz/.
[2] UNICEF. Prospects for children in the polycrisis: a 2023 global outlook. UNICEF Innocenti – Global Office of Research and Foresight; 2023.
[3] Basole A, Abraham R, Lahoti R, Kesar S, Jha M, Nath P, Mandela SN. State of working India 2021: one year of covid-19. Centre for sustainable employment. Azim Premji University; 2021.
[4] Gupta A, Malani A, Woda B. Explaining the income and consumption effects of covid in India (No. w28935). National Bureau of Economic Research; 2021.
[5] Deaton A, Kozel V. Data and dogma: the great Indian poverty debate. World Bank Res Obs 2005;20(2):177–99.
[6] Bhalla S, Bhasin K, Virmani MA. Pandemic, poverty, and inequality: evidence from India. International Monetary Fund; 2022.
[7] Betti G, Cheli B, Lemmi A, Verma V. Multidimensional and longitudinal poverty: an integrated fuzzy approach. Fuzzy set approach to multidimensional poverty measurement. 2006. p. 115–37.
[8] Van der Laan J, Kuijvenhoven L. Imputation of rounded data. Statistics Netherland 2011.
[9] Drechsler J, Kiesl H. Beat the heap: an imputation strategy for valid inferences from rounded income data. Journal of Survey Statistics and Methodology 2016;4(1): 22–42.
[10] Edochie IN, Freije-Rodriguez S, Lakner C, Herrera LM, Newhouse DL, Roy SS, Yonzan N. What do we know about poverty in India in 2017/18? Policy research working paper, 9931. World Bank Group; 2022.
[11] Newhouse DL, Vyas P. Estimating poverty in India without expenditure data: a survey-to-survey imputation approach. World Bank Group; 2019. Policy Research Working Paper, 8878.
[12] Roy SS, van der Weide R. Poverty in India has declined over the last decade but not as much as previously thought. In: Policy research working paper, vol. 9994. World Bank Group; 2022.
[13] Aguilar RAC, Diaz-Bonilla C, Fujs TH, Jolliffe DM, Lakner C, Mahler DG, Yonzan N. September 2022 update to the poverty and inequality Platform (PIP): what's new. Global poverty monitoring technical note, vol. 24. World Bank Group; 2022.
[14] World Bank. Poverty & equity brief India, october 2022. World Bank Group; 2022.
[15] Mehrotra S, Parida JK. Poverty in India is on the rise again. The Hindu; 2021. August 4.
[16] Mehrotra S, Parida JK. Stalled structural change brings an employment crisis in India. Indian J Lab Econ 2021;64(2):281–308.
[17] Himanshu, Lanjouw P, Schirmer PD. Imputation-based poverty monitoring in India post-2011. The India forum; 2024.
[18] Ram K, Yadav S. The impact of COVID-19 on poverty estimates in India: a study across caste, class and religion. Contemporary Voice of Dalit; 2021. p. 1–15.
[19] Salmeron Gomez DA, Engilbertsdottir S, Cuesta LJA, Delamónica E, Newhouse DL, Stewart D. Global trends in child monetary poverty according to international poverty lines. World Bank Group; 2023. Policy Research Working Paper, 10525.
[20] World Bank. Poverty and inequality Platform: country profile. World Bank Group; 2023. Retrieved from: https://pip.worldbank.org/.
[21] Planning Commission of India. Poverty estimates for 2011-12. New Delhi: Government of India Planning Commission; 2013.
[22] Saxegaard ECA, Coppo M, Khalil N, Kotera S, Unsal FD. Inequality and poverty in India: impact of COVID-19 pandemic and policy response. IMF Working Papers 2023;2023:147.
[23] Lemmi AA, Betti G, editors. Fuzzy set approach to multidimensional poverty measurement, vol. 3. Springer Science & Business Media; 2006.
[24] Speidel M, Drechsler J, Jolani S. The R package hmi: a convenient tool for hierarchical multiple imputation and beyond. J Stat Software 2020;95:1–48.
[25] Rubin DB. Multiple imputations in sample surveys-a phenomenological Bayesian approach to nonresponse. In: Proceedings of the survey research methods section of the American Statistical Association, vol. 1. Alexandria, VA, USA: American Statistical Association; 1978. p. 20–34.
[26] Papke LE, Wooldridge JM. Panel data methods for fractional response variables with an application to test pass rates. J Econom 2008;145(1–2):121–33.
[27] MOSPI. Periodic labour force survey (PLFS) – annual report july 2021 – June 2022. National sample survey Office, ministry of statistics and programme implementation. New Delhi: Government of India; 2023.
[28] Menon R, Nath P. A dynamic analysis of Women's labour force participation in urban India. Econ Lab Relat Rev 2022;33(4):766–85.
[29] Sundari S. Structural changes and quality of women's labour in India. Indian J Lab Econ 2020;63:689–717.
[30] Bansal I, Mahajan K. COVID-19, income shocks, and women's employment in India. Feminist Economics; 2023. p. 1–33.
[31] Deaton A. Measuring Poverty in a growing world (or measuring growth in a poor world). Rev Econ Stat 2005;87(1):1–19.
[32] Ravallion M. Measuring aggregate welfare in developing countries: how well do national accounts and surveys agree? Rev Econ Stat 2003;85(3):645–52.
[33] Drèze J, Somanchi A. View: new barometer of Indian economy fails to Reflect deprivations of poor households. The Economic Times; 2021. June 21.
[34] Pais J, Rawal V. CMIE's consumer pyramids household surveys: an assessment. The Indian forum, august 10. 2021.
[35] Sanyal S. Sources of biases in the consumer pyramids household survey. The India Forum; 2021. October 1st.
[36] Somanchi A. Missing the poor, big time: a critical assessment of the consumer pyramids household survey. 2021.
[37] Drèze J, Somanchi A. Weighty evidence? Poverty estimation with missing data. Perspectives, Ideas for India 2023. April 10.
[38] Ghatak M. Introduction to e-Symposium: estimation of poverty in India. 2022. Ideas for India, October 10.

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