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# Transition and persistence in the double burden of malnutrition and overweight or obesity: Evidence from South Africa

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## Abstract

This paper analyzes transition and persistence patterns of the Double Burden of Malnutrition (DBM) and overweight or obesity (OVOB) using South African household data spanning over 2008-2017. To test whether the DBM (the coexistence of at least one overweight or obese and one underweight individual in a household) is either a transitory or a persistent phenomenon, we use a dynamic random-effects probit model with unobserved heterogeneity. Our findings suggest that DBM is a transitory phenomenon as most double burden households over one survey period do not remain so in the subsequent waves. OVOB households remain so, implying persistence at the household level. We observe that the persistence of OVOB at the household level is mainly driven by persistence at the individual level. On the other hand, we find that the individual level rationale for the transitory status of the DBM is that underweight does not persist over time as underweight individuals do not remain so for extended periods. These widespread nutritional issues require appropriate measures such as double-duty actions.

*Keywords:* Double burden of malnutrition, Overweight, Obesity, South Africa

*JEL classification:* I10, I12, I14, 012

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# 1 Introduction

The double burden of malnutrition (hereafter, DBM or double burden) is defined as the coexistence of undernutrition (i.e., micronutrient deficiencies, underweight, or childhood stunting and wasting) and overweight, obesity, and diet-related non-communicable diseases.<sup>1</sup> Over 70% of countries face the DBM, the overwhelming majority of which are low- and middle-income countries (LMICs). In the 1990s, these were countries in Central America, Francophone Africa, South Africa, and Central Asia. Nowadays, most countries facing DBM are in sub-Saharan Africa, South Asia, and South-East Asia (Shekar and Popkin, 2020). Significant economic development and urbanization have led to a nutrition transition that has increased the prevalence of obesity in LMICs (Popkin et al., 2020). The nutrition transition is used to describe “progressive shifts in the stages of eating, drinking, and moving from traditional, nutrient-rich diets to energy-dense, nutrient-poor, ultra-processed foods, sugary calorie-laden beverages, and increased sedentary lifestyle that coincides with or is preceded by economic, demographic, and epidemiological changes” (Shekar and Popkin, 2020). Unlike developed countries, LMICs are experiencing the nutrition transition over a shorter period. The double burden is thus due to simultaneous increases in economic development and nutrition transition (Popkin, 2004; Shrimpton and Rokx, 2012). It is also driven by a decrease in undernutrition that is not proportional to the increase in overweight and obesity. As a result, undernutrition is stagnating or decreasing while obesity is increasing significantly. To investigate the double burden and its dynamics, we use the example of South Africa, where the prevalence of stunting is 27.4%, while the prevalence of overweight or obesity among women is 67.2% which is considered a “high” level (Shekar and Popkin, 2020).<sup>2</sup> These figures make South Africa a particularly interesting context to analyze. Indeed, it is the most affected country by the obesity epidemic in Sub-Saharan Africa and undernutrition persists, particularly in the poorest communities (Kimani-Murage et al., 2010; Otterbach et al., 2021).

There are several ways to measure the double burden depending on the scope. It can be assessed at the population level (a population with both undernutrition and overweight or obesity prevalent in the same community, region, or nation). It can also be assessed at the household level when household members are affected by different forms of malnutrition and at the individual level when individuals experience the simultaneous occurrence of two or more types of malnutrition, for instance, when obesity is coupled with micronutrient deficiency. Recent years have witnessed a growing academic interest in the household level approach, although studies referring to it started in the early 2000s (Doak et al., 2002; Doak et al., 2005; Garrett and Ruel, 2005). A household can be considered in DBM if there is at least one overweight or obese

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<sup>1</sup>Sometimes the DBM can be defined as the triple burden of malnutrition as it also encompasses micronutrient deficiencies. Here, we refer to the coexistence of undernutrition and overweight or obesity.

<sup>2</sup>Shekar and Popkin (2020) proposed the cut-offs: low or none, moderate, high, or very high. In the rest of Africa, the prevalence of stunting ranges from 13.6% (Mauritius) to 55.9% (Burundi) and the prevalence of overweight or obesity varies from 29% (Ethiopia) to 67.2% (South Africa).

individual and one underweight individual in the household (Doak et al., 2005; Roemling and Qaim, 2013). Alternatively, a household can also be considered in DBM if a child suffers from undernutrition with an overweight mother (Conde and Monteiro, 2014; Jehn and Brewis, 2009; Kimani-Murage et al., 2015).

This paper aims to investigate the dynamics of two nutritional statuses (DBM and overweight or obesity (OVOB))<sup>3</sup> measured at the household level. However, the dynamics of nutritional status at the household level imply intra-household and individual behaviors. The literature on the persistence of obesity focuses on its measurement at the individual level. Persistence refers to the fact that obesity is observed over a long period of people’s lives. Indeed, once obese, the body becomes used to having extra fat reserves and tries to maintain them (Rosenbaum et al., 2010). The persistence of obesity has been analyzed for American individuals, among whom most obese adults remain so for a long lifetime (Daouli et al., 2014). Individuals with persistent obesity are also those who, as children, were already obese (Gordon-Larsen et al., 2010). The persistence of overweight or obesity may also be related to genetic factors (O’Rahilly and Farooqi, 2006; Rohde et al., 2019). A double-burdened household has at least one individual who suffers from undernutrition. At the national level, the prevalence of stunting in children under five years of age has been stagnant or slowly decreasing in South Africa over the past ten years, as the prevalence of stunting was 24.9% in 2008<sup>4</sup> compared to 27.4%, according to the latest global report on obesity (Shekar and Popkin, 2020). Therefore, undernutrition is persistent at the national level, particularly for the most disadvantaged, lower-income, and food-insecure households. However, the story differs at the individual level, it is not the same people who continue to experience undernutrition and underweight might not persist over time. Indeed, according to Barker’s hypothesis, adverse nutrition in childhood (for instance, being stunted or underweight) could increase the likelihood of developing chronic and non-communicable conditions later on, such as overweight or obesity (Edwards, 2017; Barker, 1990).

This paper focuses on the persistence and transition of nutritional status at the household level. We aim to further explore the dynamics of the DBM and OVOB at the household level using survey data from South Africa. Despite the growing literature on the DBM, relatively little research has been carried out on its dynamics over time and its evolution within households. Using household surveys in Indonesia, Roemling and Qaim (2013) show that DBM is transitory at the household level as many DBM households in one period become overweight in the subsequent period. However, almost as many households remain double-burdened as there are households that experience a change in nutritional status. Although this study paves the way to study the dynamics of the DBM, it lacks an empirical model showing the causal relationship between a nutritional status in period  $t - 1$  and a nutritional status in period  $t$ . This lack of empirical analysis on

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<sup>3</sup>Hereafter, we use the term OVOB to refer to overweight or obese households, i.e. those with at least one overweight or obese individual in the household (individuals with a BMI  $\geq 25$ ). We will discuss this issue in more detail in Section 2. In this way, if we write “overweight/obese” or “overweight or obese”, it implies that we do not refer to the classification at the household level but rather to the individual level or overweight and obesity in general.

<sup>4</sup>UNICEF/WHO/World Bank Joint child malnutrition estimates expanded database: stunting, wasting and overweight (May 2021). Available at: <https://data.unicef.org/resources/dataset/malnutrition-data>. Last accessed: 26 October 2021.

the dynamics of double burden is one of the motivations of our paper. Furthermore, the mechanisms that underpin the dynamics of nutritional status are not fully understood.

To analyze the dynamics of nutritional statuses, we use a dynamic random-effects probit model with unobserved heterogeneity (Rabe-Hesketh and Skrondal, 2013; Grotti and Cutuli, 2018). We draw on data from the five waves of surveys of the National Income Dynamics Study (NIDS) implemented in South Africa. We find that DBM is a transitory phenomenon as most double burden households over one survey period do not remain so in the subsequent waves. These findings are consistent with Roemling and Qaim (2013), who find that DBM is transitory in Indonesia. We also find that OVOB households remain so, implying persistence at the household level, whereas until now, obesity persistence has been observed at the individual level. Our results also show that DBM households in  $t - 1$  are more likely to become OVOB in the follow-up periods. These dynamics at the household level stem from individual intra-household dynamics. We observe that the persistence of OVOB at the household level is mainly driven by the persistence of overweight or obesity at the individual level. Finally, the intra-household explanation for the transition from DBM to OVOB is that underweight does not persist over time since most underweight individuals become normal. On the other hand, these individuals may eventually become overweight or obese.

The contribution of this paper to the literature is threefold. **Firstly**, the dynamics of nutritional indicators at the household level have not yet been deepened, except for Roemling and Qaim (2013). Their conclusions are drawn from descriptive analysis. In this study, we explore this issue through econometrics inference to determine the transient nature of the DBM and the nutritional fate of these households in South Africa. Therefore, to the best of our knowledge, our paper is one of the first to empirically analyze the dynamics of the DBM at the household level. Analyzing the DBM at the household level is of particular interest since most studies are done at the individual level. The household level analysis allows us to study the differences between households composed solely of at least one overweight or obese individual (OVOB households) as opposed to households composed of at least one underweight and one overweight or obese individual (DBM households). The focus on households is also of particular interest because if we monitor the dynamics of the DBM at the national level by observing the prevalence of undernutrition and obesity, we do not necessarily understand what is happening at the household level and, therefore, at the individual level. For instance, if the prevalence of undernutrition and obesity at the national level increases, one does not know how this translates into household dynamics. Indeed, one may wonder if the same individuals remain overweight/obese over the years or if new individuals become overweight or obese. The same issue arises for undernutrition: when the prevalence of undernutrition is persistent at the national level, one may wonder if this persistence is due to the same individuals remaining underweight or to new individuals becoming underweight while others do not remain so? We believe this deserves a specific analysis at the household level to analyze later the implications

of individual shifts at the household level. **Secondly**, the household level analysis enables us to investigate the implications for intra-household dynamics. Indeed, this additional analysis of individual implications provides insight into the composition of double-burdened and OVOB households and how individual factors translate into household level changes. **Thirdly**, the literature on DBM often uses cross-section data ([Guevara-Romero et al., 2021](#)). We use up-to-date panel data, thus providing an updated vision of the DBM in South Africa. Panel data are particularly essential for studying dynamics and unobservable heterogeneity. In addition, given that South Africa is a middle-income country and at a relatively advanced stage of nutritional transition with a growing obesity epidemic, the case study provides a glimpse of what might happen in other Sub-Saharan African countries in their development process.

The double burden is a growing public health concern in LMICs that requires specific policy interventions, namely double-duty actions. These aim to simultaneously tackle undernutrition, overweight, obesity, and diet-related non-communicable diseases. These initiatives may consist of new policy proposals or existing interventions that address one form of malnutrition but scale up to address the multiple forms of the DBM. Some double-duty actions are meant to be implemented in the agriculture sector since this sector can contribute to the struggle against the double burden.

The rest of the paper is structured as follows. Section 2 introduces the data, provides descriptive statistics, and describes how individuals and households are categorized. Section 3 presents the empirical strategy. Section 4 reviews the results. Section 5 implements robustness analysis. A discussion of the results and policy implications are presented in Section 6. Section 7 draws the main conclusions.

## 2 Data

### 2.1 National Income Dynamics Study (NIDS)

We use five waves of the National Income Dynamics Study (NIDS) data collected by the Southern Africa Labour and Development Research Unit (SALDRU) of the University of Cape Town.<sup>5</sup> NIDS surveys examine the living conditions of South African individuals and cover issues related to economic activity, poverty and well-being, participation in the labor market, education, or health. Since 2008, surveys have been conducted every two to three years and the last available wave was conducted in 2017. The survey is based on a nationally representative sample of more than 28,000 individuals living in 7,305 households. The sample is ensured to be representative by a two-stage cluster sampling design. 400 Primary Sampling Units (PSUs) were selected from a main sample of 3,000 PSUs and randomization was conducted within representative strata of the 53 districts in South Africa.

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<sup>5</sup>NIDS portal is available at: <https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/NIDS>. Last accessed: 26 October 2021.

Surveys track individuals over time but do not track households. To build a panel of households, we first define when a household could be identified as the same unit over five consecutive periods. We categorized a household as the same unit if at least two individuals could be identified as residents in a given dwelling during the five waves. We relied on [Harris \(2016\)](#) to transform the data from a panel of individuals into a panel of households.<sup>6</sup> Based on this representative sample, we kept households with at least two members present from wave 1 to wave 5, as single-person households do not allow us to classify households according to a status. We do not consider households dissolved or formed after the first wave. We also removed households for which it was impossible to define a nutritional status in more than two waves. Finally, our sample is made up of 2,711 households spread over five waves.

## 2.2 Nutritional status

We use anthropometric measures to determine individuals' nutritional status. We use the Body Mass Index (BMI) for adults (from 19 years old in NIDS). The BMI is criticized ([Ortega et al., 2016](#)). However, it remains the most used tool ([WHO, 2020](#)). In NIDS, interviewers also measured waist circumference, which allowed us to measure the waist-to-height ratio (WHtR: waist circumference (cm)/height (cm)). To support our choice of using the BMI, we studied the correlation between BMI and WHtR, and classified individuals by nutritional status according to the WHtR and the Ashwell Shape Chart ([Ashwell, 2011](#)). The correlation matrix in [Table A.1](#) in [Appendix A](#) shows that these indicators are not statistically different. Most individuals were categorized in the same status, whether using the BMI or the WHtR. Therefore, we decided to keep the BMI measure. The thresholds are: underweight for  $\text{BMI} \leq 18.5 \text{ kg/m}^2$ ; normal if  $\text{BMI} > 18.5 \text{ kg/m}^2$  and  $< 25 \text{ kg/m}^2$ ; and overweight or obesity for  $\text{BMI} \geq 25 \text{ kg/m}^2$ . For children, we use BMI-for-age zscores. Underweight occurs when BMI-for-age  $< -2$  Standard Deviation (SD) and overweight occurs when BMI-for-age  $> 1$  SD. Children between the two thresholds are considered normal ([WHO, 2006](#)). In NIDS, anthropometric measures are performed three times. We calculate the average of the first two measurements for weight and height since the interviewers did not consider performing a third one when the first two were consistent.

To reduce the number of missing data, we made replacements as follows. Regarding the height of adults, we considered that individuals do not experience any change in height after the age of 20. According to the WHO growth charts, adolescent growth stabilizes after age 19, although this may occur earlier for girls ([De Onis, 2015](#)). We use 20 years of age as the cut-off point since even if growth has stopped before then, it can be assumed that the adult has reached his or her final height. Therefore, we replaced the heights that varied by more than 5 cm between each wave with a missing value. We also substituted the missing values for the size of adults by the average. For the weight of adults, we calculated the average of the waves framed by

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<sup>6</sup>For more details on the sampling design and the implementation of the database into a panel of households, the interested reader can refer to Section 4 of [Harris \(2016\)](#), titled *Construction a panel of households - formation and dissolution*.

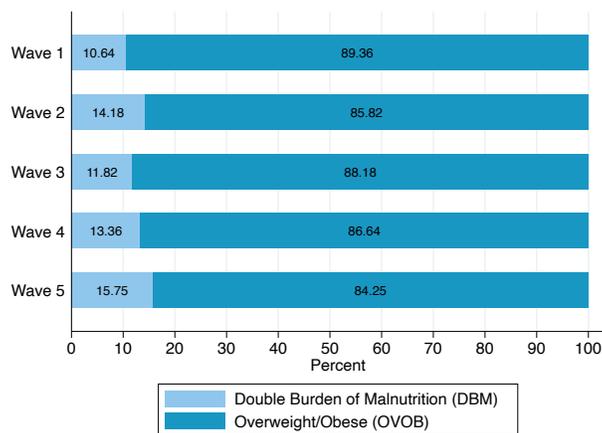
values and substituted the missing values by the average. We proceed similarly for children. To not bias the categories, we replaced the indicator of nutritional status of pregnant women and children under two years of age with missing values (Doak et al., 2005; Roemling and Qaim, 2013). To ensure that these corrections do not bias our results, we also performed regressions on “raw” data in which no replacement is made (Appendix C, Tables C.3 and C.4). Then, we categorize households according to individuals’ nutritional status.

In line with the literature, we consider three household nutritional categories: DBM (household with at least one underweight individual and at least one overweight or obese individual)<sup>7</sup>, OVOB (household with at least one overweight or obese individual and a diverse number of normal individuals, but no underweight individuals) and another nutritional status (i) normal: household entirely composed of normal individuals. ii) underweight: household with at least one underweight individual and a diverse number of normal individuals, but no overweight or obese individuals) (Doak et al., 2002; Doak et al., 2005; Roemling and Qaim, 2013).

### 2.3 Descriptive statistics

Figure 1 shows that about 13.76% of DBM and OVOB households are classified as DBM and 86.24% as OVOB across all waves. The rate of DBM households ranges from 10.64% to 15.75%, while the rate of OVOB households ranges from 84.25% to 89.36%. Most households are therefore OVOB. Table 1 displays the proportion of households that changed their nutritional status. Among DBM households, 40.89% remained so in the following survey period and 59.11% moved to the OVOB status. Among OVOB households, 90.55% were still OVOB in the next wave, while 9.45% became DBM households. The first line of Table 1 suggests that the DBM is a transitory phenomenon and the second line that OVOB is rather persistent.

Figure 1: Distribution of DBM and OVOB households



Notes: Across all waves, 13.76% are DBM households and 86.24% are OVOB households.

<sup>7</sup>We use the definition of the double burden (which includes underweight and overweight or obesity) and not the triple burden which includes micronutrient deficiencies. Although this may be considered a narrow definition, it is frequently used in the literature (Doak et al., 2002; Doak et al., 2005; Roemling and Qaim, 2013; Vaezghasemi et al., 2014).

Table 1: Transition matrix of DBM and OVOB households

Nutritional status of households in one survey period	Nutritional status of the same households in the subsequent period		
	DBM	OVOB	Total
DBM	40.89	59.11	100.00
OVOB	9.45	90.55	100.00

*Notes:* All values are in percentages.

Table 2 presents the descriptive statistics. It provides an overview of households’ characteristics, their distribution, and the differences between DBM and OVOB households. Almost 87% of household heads have at least a primary education and OVOB households are more likely to have a better-educated household head. Less than half of household heads are inactive, but DBM households are more likely to have an inactive household head than OVOB households (49.89% versus 42.57%). Approximately 76% of household heads are African and the rest are either Coloured<sup>8</sup> (11.80%), Asian/Indian (2.84%), or White (9.50%). DBM households are more likely to be African-headed than OVOB households (78.99% versus 75.19%). On the other hand, White-headed households are more likely to be OVOB than DBM (10.80% versus 1.43%). The average age of the household head is about 50 years old and DBM household heads are older than OVOB household heads. About 54% of household heads are women. Over three-fifths of the households live in urban areas and there are more DBM and OVOB households in urban areas. The average household size is about 5 members and there are more children and adults in DBM households than in OVOB households. Between two waves, more households are concerned about entries of individuals in DBM households than in OVOB households. The percentage of households with exits is about the same between DBM and OVOB households. Finally, members of OVOB households tend to be older. We describe all variables in Appendix B.

<sup>8</sup>“Coloured refers to an individual of mixed-blood that includes children/descendants from Black-White, Black-Asian, White-Asian, and Black-Coloured unions” (Tomita et al., 2015).

Table 2: Descriptive statistics

Variable	Total	DBM	OVOB	<i>t</i> -test
	Mean (SD)	Mean (SD)	Mean (SD)	<i>P</i> -value
<b>Expenditures</b>	6912.76 (544.06)	5915.97 (776.36)	7419.99 (610.10)	0.071
<b>Education of the head</b>				
No education*	13.32	19.00	12.27	0.000
Primary education*	17.42	18.58	17.29	0.538
Secondary education*	51.17	53.87	50.46	0.235
Higher education*	18.09	8.55	19.98	0.000
<b>Employment of the head</b>				
Inactive*	43.20	49.89	42.57	0.003
Unemployed*	10.29	10.45	9.55	0.568
Employed*	46.51	39.66	47.88	0.005
<b>Ethnic group of the head</b>				
African*	75.86	78.99	75.19	0.298
Coloured*	11.80	13.33	11.63	0.464
Asian/Indian*	2.84	6.25	2.38	0.141
White*	9.50	1.43	10.80	0.000
<b>Female head*</b>	54.44	54.90	56.18	0.652
<b>Age of the head</b>	50.21 (0.42)	51.93 (0.73)	50.58 (0.40)	0.066
<b>Urban*</b>	61.32	56.02	62.39	0.055
<b>Household size</b>	4.86 (0.09)	6.30 (0.19)	4.85 (0.10)	0.000
<b>Entry*</b>	32.08	45.07	31.55	0.000
<b>Exit*</b>	34.58	33.95	34.33	0.881
<b>Number of children</b>	1.57 (0.04)	2.13 (0.10)	1.57 (0.05)	0.000
<b>Mean age of household</b>	29.95 (0.42)	27.95 (0.56)	30.11 (0.44)	0.000

Notes: \* percent; standard deviations are in parentheses. Sampling weights are applied.

### 3 Empirical strategy

We study separately two nutritional statuses (DBM and OVOB) to determine whether they are transitory or persistent. The econometric specifications presented below reflect our estimation strategies.

#### 3.1 Transitory and persistent patterns

The dynamic random-effects probit model with unobserved heterogeneity takes the form:

$$y_{it} = \alpha y_{it-1} + \beta \bar{\mathbf{Z}}_{it} + c_i + u_{it} \quad (1)$$

for household  $i$  ( $i = 1, \dots, N$ ), and period  $t$  ( $t = 1, \dots, T_i$ ), where  $y_{it}$  is the nutritional status ( $DBM_{it}$  or  $OVOB_{it}$ ) of household  $i$  in  $t$ ,  $y_{it-1}$  the nutritional status ( $DBM_{it-1}$  or  $OVOB_{it-1}$ ) in  $t - 1$ ,  $\bar{\mathbf{Z}}_{it}$  a set of explanatory variables,  $c_i$  the household-specific unobserved effect, and  $u_{it}$  the idiosyncratic error term normally distributed with mean 0 and variance  $\sigma_u^2$ .  $y_{it-1}$  captures genuine state dependence, i.e., the effect exerted by the nutritional status of the previous period on the nutritional status in  $t$ . All explanatory variables  $\bar{\mathbf{Z}}_{it}$  are listed in Appendix B. The variables are based on the literature and include several demographic and

socioeconomic factors (Garrett and Ruel, 2005; Guevara-Romero et al., 2021). Income is also often used as a determinant of the DBM. Some studies report that compared to underweight households, DBM households have higher incomes (Doak et al., 2005; Tzioumis and Adair, 2014), while other studies have found no significant difference between DBM and normal households (Kosaka and Umezaki, 2017). Households whose heads have received a higher level of education are less likely to face DBM (Fongar et al., 2019; Vaezghasemi et al., 2014) and DBM households tend to be male-headed (Roemling and Qaim, 2013; Vaezghasemi et al., 2014). We use the variables related to the socioeconomic status (monthly household expenditures, educational attainment, and employment status of the household head), the household’s living area (urban vs. rural), the ethnic group, gender and age of the head, and the household composition (household size, entry or exit of individuals between waves, number of children, and mean age of household members and its square).

The estimation of Eq. (1) requires further exploration. In particular, some specific features inherent to the dynamic probit model are worth discussing, including unobserved heterogeneity and initial conditions. Many unobserved factors cannot be captured by control variables such as genetic differences. Most households are composed of individuals belonging to the same family and share similar genes. There are genetic factors that increase the likelihood of being overweight or obese. Therefore, it is crucial to control for such factors. In addition, omitted variables may be correlated with observed and unobserved factors. For instance, the nutritional status of a household in the first period can be correlated with unobserved factors. Also, a household’s location in the first period may be correlated with the proximity of a fast-food restaurant or nearby supermarkets containing highly processed or hyper-caloric food products. These factors influence the nutritional status of individuals and thus the household’s status. As a result, unobserved heterogeneity and initial condition problem must be accounted for.

The retained specification is the Wooldridge (2005) model, which addresses these issues. To control for unobserved heterogeneity and the initial condition problem, Wooldridge (2005) proposes to include time-varying explanatory variables at each period (except the initial period). Rabe-Hesketh and Skrondal (2013) controlled for the unobserved effects by including within-unit averages computed on the time-varying explanatory variables and by augmenting the model specification with the initial period of the dependent variable and the initial period of the time-varying explanatory variables. Their model assumes the strict exogeneity of the explanatory variables. We assume that this condition is met since it is unlikely that there is a retroactive effect of the status in  $t$  on past or future explanatory variables. We also readily assume the predeterminedness of initial variables. Relying on Rabe-Hesketh and Skrondal (2013) and Grotti and Cutuli (2018), the household-specific unobserved effect takes the form:

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \mathbf{Z}_{i0} + \alpha_3 \bar{\mathbf{Z}}_l + \epsilon_i \quad (2)$$

where  $y_{i0}$  is the initial value of the dependent variable ( $DBM_{i0}$  or  $OVOB_{i0}$ ),  $\mathbf{Z}_{i0}$  the initial values of the time-

varying explanatory variables,  $\bar{Z}_i$  the within-unit averages of the time-varying explanatory variables, and  $\epsilon_i$  a unit-specific time-constant error term (assumed to be normally distributed with mean 0 and variance  $\sigma_\epsilon^2$ ). The variables used to estimate unobserved heterogeneity are time-varying, which include monthly household expenditures, employment status, gender and age of the household head, and household composition variables. Controlling for unobserved heterogeneity allows us to distinguish the effects of unobserved heterogeneity from genuine state dependence of the nutritional status in  $t - 1$ . Assuming that unobserved heterogeneity is captured by  $c_i$ , then the lagged value of the dependent variable can be interpreted as a genuine state dependence. Eq. (1) is estimated using a dynamic random effects probit model and conditional maximum likelihood estimator (Wooldridge, 2005; Rabe-Hesketh and Skrondal, 2013; Grotti and Cutuli, 2018). In this estimation, we employ mean-variance adaptive Gauss-Hermite quadrature with 12 integration points following Grotti and Cutuli (2018). We expect to observe a state dependence for the OVOB status, meaning a positive sign of the lagged variable’s coefficient. We also expect to observe the transient nature of the DBM.

The dynamic random effects probit model allows computing expected transition probabilities and persistence. The probabilities are computed from the estimated coefficients and used to determine the probabilities of entering, staying in, or leaving a nutritional status. The estimated entry rate is:

$$Pr(1|0) = Pr(y_{it} = 1 | y_{it-1} = 0, \mathbf{X}) = \Phi[\gamma\mathbf{X}] \quad (3)$$

The estimated persistent rate is:

$$Pr(1|1) = Pr(y_{it} = 1 | y_{it-1} = 1, \mathbf{X}) = \Phi[\alpha + \gamma\mathbf{X}] \quad (4)$$

where  $y_{it}$  is the nutritional status ( $DBM_{it}$  or  $OVOB_{it}$ ),  $\mathbf{X}$  includes the time-constant explanatory variables, the time-varying explanatory variables, and all the variables capturing unobserved heterogeneity,  $\gamma$  is a vector of associated coefficients,  $\alpha$  is the coefficient associated with  $y_{it-1}$ , and  $\Phi$  represents the standard normal cumulative distribution function. The exit rate is derived from the estimated persistent rate and is computed as  $1 - Pr(1|1)$ . We expect to observe a high persistence rate for the OVOB status, which would provide evidence that this status is persistent. We also expect to observe a low persistence rate and a high exit rate for the DBM, which would show that the DBM is transitory.

### 3.2 What do DBM households become?

Now we study what happens to households whose status is transitory. Initially, we assume that DBM is a transitory phenomenon. Therefore, this status may be a transition to OVOB. There are two alternatives for a DBM household to change nutritional status to OVOB: the underweight individual(s) become normal or overweight/obese. In both cases, DBM households in  $t - 1$  will now be considered OVOB in  $t$ . However, it is also possible that the individual(s) formerly considered underweight leaves the household. If we take the

example of an underweight individual who leaves, then, in  $t$ , if other individuals keep the same status, the household will be considered OVOB. However, this change will not be related to a change in the nutritional status of individuals but rather to a change in household size or composition. Therefore, to avoid bias in our estimates, we control for the household composition effect. To observe what happens to DBM households, we run the following regression:

$$OVOB_{it} = \alpha_1 OVOB_{it-1} + \alpha_2 DBM_{it-1} + \beta \bar{Z}_{it} + c_i + u_{it} \quad (5)$$

for household  $i = 1, \dots, N$ , and  $t = 1, \dots, T_i$ , where  $\bar{Z}_{it}$  and  $c_i$  are the same variables as in Eqs. (1) and (2). With  $DBM_{it-1}$  and  $OVOB_{it-1}$  the status of the household  $i$  in  $t - 1$  and,  $u_{it}$  the idiosyncratic error term normally distributed with mean 0 and variance  $\sigma_u^2$ . If the double burden is transient to the OVOB status, we should observe a positive sign associated with the coefficient of the variable  $DBM_{it-1}$ . As in Eq. (1), we use a dynamic random effects probit model following [Grotti and Cutuli \(2018\)](#) method.

## 4 Results

### 4.1 The dynamics of nutritional statuses

Table 3 provides the results of the average marginal effects from the estimation of Eq. (1). Column (1) reports the results for the DBM, while column (2) reports the results for OVOB. In column (1), the coefficient of DBM in  $t - 1$  is positive and statistically significant, meaning that the likelihood of a household to face the DBM increases by 3.9% if the household was double burdened in the previous period. The coefficient indicates genuine state dependence. It implies that a DBM household in  $t - 1$  is more likely to stay in DBM in  $t$ . We also observe a statistically significant and positive effect of the initial condition DBM in  $t_0$ . This indicates that a DBM household in the first period is more likely to remain so in  $t$ . Considering household characteristics, the likelihood of being in DBM decreases with the level of education. The likelihood of a Coloured or Asian/Indian household head being in DBM increases compared to an African household. Finally, the likelihood of being in DBM increases when the household lives in an urban area. In this model, we also controlled for household composition. The more individuals and children in the household, the more likely a household will be considered in DBM. Also, the likelihood of being in DBM increases with the mean age of the household up to a threshold (about 50 years old) and reverses beyond, which shows non-linearity. On the other hand, entries and exits do not have a significant impact. This shows that the household composition is probably not endogenous. The entry or exit from the household does not affect the results.

In column (2), the average marginal effect associated with OVOB in  $t - 1$  is positive and statistically significant. The likelihood of a household being OVOB increases by 10.2% if the household was OVOB in the

previous period. Accordingly, once controlled for initial conditions and net of unobserved heterogeneity, the coefficient indicates genuine state dependence. The coefficient of the OVOB variable in  $t_0$  is also positive and significant. The probability of being OVOB in  $t$  is lower by 2% for urban households compared to their rural counterparts. As for ethnicity, African households are more likely to be considered OVOB. The likelihood of being OVOB increases with education level. Finally, the likelihood of a household being OVOB decreases with the number of children.

Table 3: Average marginal effects from the dynamic probit model

	(1) DBM	(2) OVOB
DBM in $t - 1$	0.039*** (0.012)	
DBM in $t_0$	0.340*** (0.018)	
OVOB in $t - 1$		0.102*** (0.015)
OVOB in $t_0$		0.426*** (0.015)
Expenditures	0.015** (0.006)	-0.010 (0.007)
Primary education	0.003 (0.010)	0.008 (0.013)
Secondary education	0.002 (0.010)	0.018 (0.013)
Higher education	-0.025* (0.013)	0.031* (0.018)
Unemployed	0.010 (-0.014)	-0.023 (0.017)
Employed	-0.013 (0.009)	-0.003 (0.012)
Urban	0.023*** (0.008)	-0.020** (0.010)
Coloured	0.027*** (0.010)	-0.045*** (0.013)
Asian/Indian	0.109*** (0.036)	-0.123*** (0.040)
White	-0.028 (0.025)	-0.068** (0.033)
Female head	-0.000 (0.009)	0.015 (0.012)
Age of the head	-0.000 (0.000)	0.001 (0.001)
Household size	0.017*** (0.004)	0.002 (0.005)
Entry	0.011 (0.008)	-0.006 (0.010)
Exit	-0.004 (0.008)	0.005 (0.010)
Number of children	0.017*** (0.006)	-0.019** (0.008)
Mean age of household	0.009*** (0.003)	-0.003 (0.003)
Mean age of household squared	-0.001** (0.001)	0.000 (0.000)
Initial values ( $Z_{t_0}$ )	Yes	Yes
Averages ( $\bar{Z}_t$ )	Yes	Yes
Observations	9,514	9,514
N. households	2,693	2,693
Log-likelihood	-2,743.259	-4,002.224
Wald chi2(42)	1,022.94	1,786.82
Prob > chi2	0.000	0.000

Notes: Standard deviations are in parentheses. The reference categories of the explanatory variables are no education; inactive; rural; and African.

\*\*\*  $p < 0.01$  ; \*\*  $p < 0.05$  ; \*  $p < 0.1$ .

Table 4 presents the predicted probabilities of each nutritional status and the expected duration spent in a status. A household has an average probability of entering DBM of about 10.57%. The average probability of being in DBM at time  $t$  conditional of having been in the status at time  $t - 1$  is about 14.33%. Despite the positive and statistically significant marginal effect in column (1) of Table 3, these results suggest that DBM is not a persistent phenomenon as the average probability of exiting DBM is about 85.67%. Finally, the expected average duration spent in DBM is 1.17 waves, which means that a DBM household will stay in this status for an average of just over one wave. Therefore, it is very likely that most DBM households will experience a change in nutritional status over time. The second row of Table 4 shows that a household has an average probability of entering the OVOB category of 68.11%. OVOB households have a very high probability of staying in this category (78.47%) and, therefore, not moving out (21.53%). Lastly, the expected mean duration is about 4.65 waves, which means that an OVOB household spends almost all five waves in this status. The predicted probabilities are consistent with the results in Table 3: OVOB is a persistent nutritional status since a genuine state dependence is established.

Table 4: Predicted probabilities

Nutritional status	Dynamics			
	Entry	Persistence	Exit	Mean duration
DBM	10.57	14.33	85.67	1.17
OVOB	68.11	78.47	21.53	4.65

*Notes:* Probabilities can be interpreted as entry, persistence and exit rates:  $Pr(1|0)$  ;  $Pr(1|1)$  ;  $Pr(0|1)$ . Mean duration:  $1/Pr(0|1)$ .

Table 5 reports the predicted probabilities of household characteristics. When the household head has received higher education, the probability that the household exits DBM is about 88.48% compared to 85.53% for households with an uneducated head. Households that have an employed head have the highest probability of exiting the DBM and the lowest persistence. The rural area is also associated with the highest probability of exiting the DBM (86.92% versus 84.14%). White-headed households are less likely to remain in DBM (10.33%), less likely to enter (7.43%), and more likely to leave (89.67%). Finally, female-headed households are almost as likely to remain in DBM. Regarding OVOB, households whose head has a higher level of education, is inactive, an African, or lives in a rural area are more likely to remain OVOB. Whatever the category, persistence rates associated with DBM are relatively low compared to OVOB. This reinforces our initial findings on the persistence of OVOB and the transitory nature of the DBM.

Table 5: Predicted probabilities of categorical variables

Category	Dynamics			
	Entry	Persistence	Exit	Mean duration
<b>DBM</b>				
<b>Education of the head</b>				
No education	10.67	14.47	85.53	1.17
Primary education	10.93	14.80	85.20	1.17
Secondary education	10.82	14.66	85.33	1.17
Higher education	8.36	11.52	88.48	1.13
<b>Employment status of the head</b>				
Inactive	10.92	14.78	85.22	1.17
Unemployed	11.86	15.96	84.04	1.19
Employed	9.72	13.26	86.74	1.15
<b>Area</b>				
Rural	9.59	13.08	86.92	1.15
Urban	11.80	15.86	84.14	1.19
<b>Ethnic group</b>				
African	10.01	13.65	86.35	1.16
Coloured	12.55	16.85	83.15	1.20
Asian/Indian	20.61	26.60	73.40	1.36
White	7.43	10.33	89.67	1.11
<b>Gender of the head</b>				
Male	10.59	14.36	85.64	1.17
Female	10.55	14.31	85.69	1.17
<b>OVOB</b>				
<b>Education of the head</b>				
No education	66.41	77.13	22.87	4.37
Primary education	67.46	77.98	22.02	4.54
Secondary education	68.63	78.92	21.08	4.74
Higher education	70.26	80.21	19.79	5.00
<b>Employment status of the head</b>				
Inactive	68.50	78.80	21.20	4.72
Unemployed	65.58	76.43	23.57	4.24
Employed	68.11	78.48	21.52	4.65
<b>Area</b>				
Rural	69.27	79.39	20.61	4.85
Urban	66.74	77.36	22.64	4.42
<b>Ethnic group</b>				
African	69.42	79.55	20.45	4.89
Coloured	63.73	74.94	25.06	3.99
Asian/Indian	54.22	66.80	33.20	3.01
White	60.97	72.63	27.37	3.65
<b>Gender of the head</b>				
Male	66.88	77.48	22.52	4.44
Female	68.75	78.99	21.01	4.76

Notes: Probabilities can be interpreted as entry, persistence and exit rates:  $Pr(1|0)$ ;  $Pr(1|1)$ ;  $Pr(0|1)$ . Mean duration:  $1/Pr(0|1)$ .

Table 6 below summarizes estimates for rural and urban subsamples. Rural households in DBM in  $t - 1$  are less likely to remain in DBM than urban households. This result is consistent with the positive sign associated with the urban variable and the magnitude of the coefficient associated with DBM in  $t - 1$  in Table 3. For OVOB households, the difference in percentage points between the two areas is greater, but the results remain the same since OVOB households in rural areas are more likely to remain so.

Table 6: Average marginal effects, urban and rural sample

	Urban		Rural	
	DBM (1)	OVOB (2)	DBM (3)	OVOB (4)
DBM in $t - 1$	0.042** (0.017)		0.035** (0.017)	
OVOB in $t - 1$		0.088*** (0.021)		0.111*** (0.020)
Explanatory variables ( $\bar{Z}_{it}$ ) <sup>1</sup>	Yes	Yes	Yes	Yes
Initial values ( $Z_{i0}$ )	Yes	Yes	Yes	Yes
Averages ( $\bar{Z}_t$ )	Yes	Yes	Yes	Yes
Observations	4,581	4,581	4,933	4,933
N. households	1,353	1,353	1,341	1,341
Log-likelihood	-1,241.097	-1,766.870	-1,454.286	-2,196.200
Wald chi2(41)	503.07	886.11	562.32	903.52
Prob > chi2	0.000	0.000	0.000	0.000

Notes: <sup>1</sup> Except urban. Standard deviations are in parentheses.  
\*\*\*  $p < 0.01$  ; \*\*  $p < 0.05$  ;  $p < 0.1$ .

## 4.2 Addressing potential endogeneity issues

We suspect the presence of endogeneity for two variables: household expenditures and the labor market status of the household head. For instance, unobserved variables could determine both nutritional status and expenditures. Also, for the employment status of the household head, individuals may be so malnourished (either under- or overweight) that this may affect their job seeking. To address potential endogeneity bias, we estimate the dynamic random-effects probit model with two alternatives: i) removing the variables suspected of endogeneity (Columns (1) and (2) of Table 7) and ii) keeping only the initial values of these variables (Columns (3) and (4) of Table 7). By including only the initial values of the presumed endogenous variables, we argue that they are predetermined since they are likely to be uncorrelated to present and future values.<sup>9</sup>

Table 7 displays the results of the dynamic random-effects probit model, taking into account the potential endogeneity of some explanatory variables. According to columns (1) and (3), the likelihood of a household to face the double burden increases by 4.1% or 4.4% if the household was double burdened in the previous period, which is roughly similar to the main results (3.9% in Table 3). The magnitude of the coefficients associated with the lagged OVOB variable is slightly different, but the findings remain similar. Most coefficients of explanatory variables are also quite similar to those in Table 3 for both DBM and OVOB. The predicted probabilities are provided in Table 8 and values remain similar. As a result, even when correcting for the assumed endogeneity of some explanatory variables, the conclusions remain consistent.

<sup>9</sup>We thank the editor for suggesting this approach.

Table 7: Average marginal effects from the dynamic probit model with endogeneity

	(1)	(2)	(3)	(4)
	DBM	OVOB	DBM	OVOB
DBM in $t - 1$	0.041*** (0.012)		0.044*** (0.013)	
DBM in $t_0$	0.337*** (0.018)		0.333*** (0.19)	
OVOB in $t - 1$		0.113*** (0.015)		0.114*** (0.016)
OVOB in $t_0$		0.428*** (0.016)		0.422*** (0.016)
Primary education	-0.001 (0.010)	0.015 (0.013)	0.003 (0.010)	0.015 (0.013)
Secondary education	-0.004 (0.010)	0.038*** (0.013)	0.005 (0.010)	0.030** (0.014)
Higher education	-0.036*** (0.012)	0.080*** (0.016)	-0.021 (0.014)	0.054*** (0.018)
Urban	0.018** (0.007)	0.000 (0.010)	0.019** (0.008)	-0.012 (0.010)
Coloured	0.024** (0.010)	-0.034*** (0.013)	0.021** (0.010)	-0.037*** (0.014)
Asian/Indian	0.089*** (0.033)	-0.060* (0.036)	0.096*** (0.036)	-0.11** (0.042)
White	-0.045** (0.021)	0.011 (0.027)	-0.042* (0.024)	-0.039 (0.032)
Female head	-0.000 (0.009)	0.019 (0.012)	-0.002 (0.010)	0.021 (0.012)
Age of the head	-0.000 (0.000)	0.001*** (0.001)	-0.000 (0.000)	0.001* (0.001)
Household size	0.018*** (0.004)	0.002 (0.005)	0.018*** (0.004)	0.001 (0.005)
Entry	0.014* (0.008)	-0.010 (0.010)	0.015* (0.008)	-0.015 (0.011)
Exit	-0.004 (0.008)	0.006 (0.010)	-0.004 (0.008)	0.006 (0.010)
Number of children	0.017*** (0.006)	-0.018** (0.008)	0.017*** (0.006)	-0.017** (0.008)
Mean age of household	0.010*** (0.003)	-0.004 (0.003)	0.011*** (0.003)	-0.006 (0.004)
Mean age of household squared	-0.001** (0.001)	0.000 (0.000)	-0.001** (0.001)	0.000 (0.000)
Expenditures in $t_0$			-0.007 (0.005)	0.026*** (0.006)
Unemployed in $t_0$			-0.010 (0.011)	0.025* (0.014)
Employed in $t_0$			-0.015* (0.008)	0.025** (0.010)
Initial values ( $Z_{i0}$ )	Yes	Yes	Yes	Yes
Averages ( $\bar{Z}_t$ )	Yes	Yes	Yes	Yes
Observations	9,648	9,648	8,624	8,624
N. households	2,701	2,701	2,396	2,396
Log-likelihood	-2,801.015	-4,111.871	-2,473.374	-3,650.184
Wald chi2(33) or chi2(36) <sup>1</sup>	1,028.32	1,795.44	952.03	1,650.73
Prob > chi2	0.000	0.000	0.000	0.000

Notes: <sup>1</sup> Wald chi2(33) in Columns (1) and (2) and Wald chi2(36) in Columns (3) and (4). Standard deviations are in parentheses. The reference categories of the explanatory variables are no education; inactive; rural; and African.

\*\*\*  $p < 0.01$  ; \*\*  $p < 0.05$  ; \*  $p < 0.1$ .

Table 8: Predicted probabilities with endogeneity

Nutritional status	Dynamics			
	Entry	Persistence	Exit	Mean duration
Columns (1) and (2)				
DBM	10.50	14.48	85.52	1.17
OVOB	67.40	78.87	21.13	4.73
Columns (3) and (4)				
DBM	10.50	14.85	85.15	1.17
OVOB	67.17	78.73	21.27	4.70

Notes: Probabilities can be interpreted as entry, persistence and exit rates:  $Pr(1|0)$  ;  $Pr(1|1)$  ;  $Pr(0|1)$ . Mean duration:  $1/Pr(0|1)$ .

### 4.3 The fate of DBM households

The transition matrix in Table 1 shows that more than half of DBM households in  $t - 1$  become OVOB in  $t$ . To study what happens to DBM households from one period to another, we use model (5). Table 9 reports the results. The coefficient of DBM in  $t - 1$  is positive and statistically significant, meaning that the likelihood of a household to be OVOB in  $t$  increases by 9.4% if the household was double burdened in the previous period. We also notice that the average marginal effect of OVOB in  $t - 1$  is slightly higher than the DBM. In other words, an OVOB household in  $t - 1$  is more likely to be OVOB in  $t$  than a DBM household. Based on these results, the double burden of malnutrition can be considered transient to OVOB since most households in DBM become OVOB over time.

Table 9: Average marginal effects

	OVOB
OVOB in $t - 1$	0.138*** (0.013)
DBM in $t - 1$	0.094*** (0.013)
Explanatory variables ( $\bar{Z}_i$ )	Yes
Initial values ( $Z_{i0}$ )	Yes
Averages ( $\bar{Z}_t$ )	Yes
Observations	9,514
N. households	2,693
Log-likelihood	-3,977.368
Wald chi2(42)	1,835.96
Prob > chi2	0.000

Notes: Standard deviations are in parentheses. \*\*\*  $p < 0.01$  ; \*\*  $p < 0.05$  ;  $p < 0.1$ .

## 5 Robustness checks

In this section, we conducted three types of robustness. We use other anthropometric indicators for children, different household size, and “raw” data.

## 5.1 Alternative anthropometric indicators for children

Formerly, we used BMI-for-age to assess the nutritional status of children. For the purpose of robustness with alternative anthropometric measures, we use weight-for-age. The results are provided in Tables 10 and 11. The findings are similar to the main results. The likelihood of a household facing the DBM increases by 3.6% (3.9% for the main results) if the household was double burdened in the previous period. On the other hand, an OVOB household in  $t - 1$  is more likely to remain so in  $t$ : the likelihood of a household being OVOB increases by 12.0% (10.2% for the main results) if the household was OVOB in the previous period. Table 11 presents the predicted probabilities. A household has an average probability of entering the OVOB category of 65.50%, staying in of 77.71%, and moving of 22.29% (versus 68.11%, 78.47%, and 21.53% for the main results). The predicted probabilities of the DBM category are also similar to the main results. The entry rate is 9.27%, the persistence rate is 12.72%, and the exit rate is 87.28%. To check further robustness, we use nutritional status depending on the age of the children. We distinguished children as follows: for children under five, we use the weight-for-height and the BMI-for-age for children between 5 and 19 years. These results are available in Tables C.1 and C.2 in Appendix C. The conclusions remain unchanged. We also used two additional indicators for child anthropometry: weight-for-height and height-for-age. The results remain similar and are available upon request.

Table 10: Average marginal effects from the dynamic probit model, weight-for-age for children

	(1)	(2)
	DBM	OVOB
DBM in $t - 1$	0.036*** (0.012)	
OVOB in $t - 1$		0.120*** (0.015)
Explanatory variables ( $\bar{Z}_{it}$ )	Yes	Yes
Initial values ( $Z_{i0}$ )	Yes	Yes
Averages ( $\bar{Z}_t$ )	Yes	Yes
Observations	9,277	9,277
N. households	2,657	2,657
Log-likelihood	-2,483.362	-3893.840
Wald chi2(42)	908.20	1,845.07
Prob > chi2	0.000	0.000

Notes: Standard deviations are in parentheses.

\*\*\*  $p < 0.01$  ; \*\*  $p < 0.05$  ; \*  $p < 0.1$ .

Table 11: Predicted probabilities, weight-for-age for children

Nutritional status	Dynamics			
	Entry	Persistence	Exit	Mean duration
DBM	9.27	12.72	87.28	1.15
OVOB	65.50	77.71	22.29	4.49

Notes: Probabilities can be interpreted as entry, persistence and exit rates:  $Pr(1|0)$  ;  $Pr(1|1)$  ;  $Pr(0|1)$ . Mean duration:  $1/Pr(0|1)$ .

## 5.2 Households with less than five individuals

In this check, we limit the sample to a number of individuals in each household. Household size may influence the way we categorize a status. The larger the household, the more likely it is to be composed of at least one overweight or obese individual and one underweight individual. According to the descriptive statistics in Table 2, the average household size is about five individuals (4.86). We remove households with more than five individuals across all five waves and estimate the dynamic probit model. The results are available in Tables 12 and 13. We find the same signs and significance. Although the magnitude of the predicted probabilities is slightly different, the results are also similar. The DBM is a transitory phenomenon: persistence rate of 9.52%; entry rate of 5.16%; and exit rate of 90.48%. On the other hand, OVOB is still persistent. The conclusions for this sample remain consistent.

Table 12: Average marginal effects from the dynamic probit model, household with less than five individuals

	(1)	(2)
	DBM	OVOB
DBM in $t - 1$	0.049** (0.020)	
OVOB in $t - 1$		0.104*** (0.022)
Explanatory variables ( $\bar{Z}_{it}$ )	Yes	Yes
Initial values ( $Z_{i0}$ )	Yes	Yes
Averages ( $\bar{Z}_l$ )	Yes	Yes
Observations	4,151	4,151
N. households	1,222	1,222
Log-likelihood	-775.063	-1,513.820
Wald chi2(42)	303.85	733.56
Prob > chi2	0.000	0.000

Notes: Standard deviations are in parentheses.

\*\*\*  $p < 0.01$  ; \*\*  $p < 0.05$  ; \*  $p < 0.1$ .

Table 13: Predicted probabilities, households with less than five individuals

Nutritional status	Dynamics			
	Entry	Persistence	Exit	Mean duration
DBM	5.16	9.52	90.48	1.11
OVOB	71.36	81.83	18.17	5.50

Notes: Probabilities can be interpreted as entry, persistence and exit rates:  $Pr(1|0)$  ;  $Pr(1|1)$  ;  $Pr(0|1)$ . Mean duration:  $1/Pr(0|1)$ .

## 5.3 Raw anthropometric data

In data processing, we slightly modified the height and weight values for adults and the BMI-for-age values for children. We perform the same estimates with “raw” data to ensure that these changes do not affect the results. In this data, we do not replace missing values. The results are consistent. All results are available in Tables C.3 and C.4 in Appendix C.

## 6 Discussion

### 6.1 OVOB: A persistent status

We find evidence of the persistence of OVOB. Some drivers that explain it are household characteristics. For example, households living in rural areas are more likely to remain OVOB, which is inconsistent with previous findings that often associate obesity with urban areas (Adeboye et al., 2012; Ziraba et al., 2009). This result may be due to the lack of resources or care options facing rural households. These factors disadvantage rural households, which would suffer from overweight or obesity. African-headed households are also the most likely to remain OVOB. In South Africa, being overweight is not perceived in the same way among ethnic groups (Cois and Day, 2015). A larger waist is often seen as a sign of beauty, prosperity, and good health among the African population. Therefore, this perception often presents in women can be a factor explaining overweight and obesity (Micklesfield et al., 2013). In addition, the higher the education of the household head, the more likely OVOB persists. This positive relationship between education and overweight or obesity is often observed in LMICs, where obesity is more prevalent in the better-off socioeconomic groups (Dinsa et al., 2012). At the household level, all these characteristics contribute to explain the persistence of OVOB.

Table 14 describes individuals' nutritional statuses dynamics for households that remain OVOB from one period to the next. We argue that the persistence of overweight and obesity at the individual level induces persistence at the household level. We observed that almost 84% of individuals remain overweight or obese. However, the individual dynamics differ depending on age. In households that remain OVOB, 91.78% of adults remain overweight or obese versus 55.69% for children and the remaining children become normal (44.31%). For the other individuals composing an OVOB household, i.e. normal individuals, most of them remain in this category (82.62%). As a result, intra-household dynamics contribute to explain the persistence of the OVOB status at the household level.

Table 14: Transition matrix of individuals' nutritional status in households that remain OVOB

Nutritional status of individuals in one survey period		Nutritional status of the same individuals in subsequent period		
		Normal	Overweight/Obese	Total
<b>Adults</b>	Normal	76.63	23.37	100.00
	Overweight/Obese	8.22	91.78	100.00
<b>Children</b>	Normal	87.16	12.84	100.00
	Overweight/Obese	44.31	55.69	100.00
<b>Both</b>	Normal	82.62	17.38	100.00
	Overweight/Obese	16.01	83.99	100.00

Notes: All values are in percentages.

## 6.2 The double burden: A transitory status

We find that a household with at least one overweight or obese and one underweight individual does not stay in this situation for long. For instance, the higher the household head’s education, the less likely the household will face DBM. This negative relationship between DBM and education is often identified in the literature and can be explained by differences in health and nutrition knowledge (Fongar et al., 2019; Vaezghasemi et al., 2014; Kosaka and Umezaki, 2017). Like education, the urban area appears to be more conducive to the transitory nature of the DBM (Jones et al., 2016; Kosaka and Umezaki, 2017). DBM has been described as an urban phenomenon associated with a wider variety of food choices, more sedentary lifestyles, the westernization of diets, and eating environments dominated by supermarkets and fast-food restaurants (Doak et al., 2002; Roemling and Qaim, 2013). In terms of ethnicity, White households are the least likely to experience DBM for multiple periods. Finally, female-headed households are less likely to remain in the DBM category, which is consistent with the findings of Roemling and Qaim (2013) and Vaezghasemi et al. (2014).

We also find evidence that a large proportion of DBM households switch to the OVOB category from  $t - 1$  to  $t$ . Indeed, if a household formerly in DBM moves to the OVOB status, this implies that the underweight individual(s) have either become normal or become overweight or obese. Therefore, the change in individual status leads to the transition at the household level. To examine intra-household dynamics, we provide Table 15, which details changes in individual status for households transitioning from DBM to OVOB. The transition is due to underweight individuals becoming normal since 82.79% of underweight individuals in  $t - 1$  are now considered normal in  $t$ , whether they are children (81.56%) or adults (84.38%). On the other hand, adults are more likely to have persistent overweight or obesity than children in households that transitioned (89.13% versus 43.36%). Regarding other individuals, most normal individuals remain so (79.18%) and those who become overweight or obese are more likely to be adults (26.73% versus 15.64%). We also find a nutritional improvement for most children as 56.05% transitioned from overweight or obese to normal.

To summarize, the individual level rationale for the transitional status of the DBM is that underweight does not persist over time as underweight individuals become normal regardless of age. It may be considered an improvement or a recovery from being underweight for some individuals. Nevertheless, it is not for others as some remain trapped in overweight and obesity. Moreover, if we refer to the Barker hypothesis, it is not excluded that underweight children who become normal develop chronic and non-communicable conditions later (Barker, 1990; Edwards, 2017). According to the Barker hypothesis, adverse nutrition in early life can increase susceptibility to the metabolic syndrome, including overweight and obesity later on. Therefore, this can contribute to the growing obesity epidemic over time.

These findings are helpful to compare our results to South Africa’s national dynamics where at the macro

level, while obesity is spreading, undernutrition persists. Following households over several periods, we have seen that DBM at the household level is a transitory phenomenon. At the individual level, we explain it by the fact that underweight individuals do not remain so over time. Hence, while obesity is persistent at the national level and by following individuals over multiple survey periods, on the contrary undernutrition does not persist for the same individuals. It represents a key result of our study. When undernutrition persists in a country, it is not necessarily the same individuals who are underweight throughout their lives but rather new individuals who might become underweight over time. This contributes to explain the persistence of undernutrition at the national level in South Africa, while at the individual level, it is not the same individuals who remain underweight.

Table 15: Transition matrix of individual’s nutritional status in households that transitioned from DBM to OVOB

Nutritional status of individuals in one survey period		Nutritional status of the same individuals in subsequent period			
		Underweight	Normal	Overweight/Obese	Total
<b>Adults</b>					
	Underweight	0.00	84.38	15.62	100.00
	Normal	1.24	72.03	26.73	100.00
	Overweight/Obese	0.14	10.73	89.13	100.00
<b>Children</b>					
	Underweight	0.00	81.56	18.44	100.00
	Normal	0.97	83.39	15.64	100.00
	Overweight/Obese	0.59	56.05	43.36	100.00
<b>Both</b>					
	Underweight	0.00	82.79	17.21	100.00
	Normal	1.04	79.18	19.78	100.00
	Overweight/Obese	0.22	20.23	79.55	100.00

*Notes:* All values are in percentages.

### 6.3 Policy implications

These issues call for appropriate measures to address the detrimental effects of South Africa’s double burden. Our results are valid for South Africa. However, the same findings have been observed for Indonesia (Roemling and Qaim, 2013). Therefore, without generality, this issue may not be specific to these countries exclusively, and instead, it could also apply to some LMICs affected by the DBM. Overall, dealing with this issue involves implementing actions that limit malnutrition in all its forms. The concept of double-duty actions was introduced in the 2015 Global Nutrition Report (IFPRI, 2015) and then gradually adopted in the nutrition research field to address this public health issue. These actions include interventions, programs and policies that have the potential to simultaneously reduce the risk of both undernutrition and overweight,

obesity, or diet-related NCDs ([WHO, 2017](#)). Double-duty actions are not necessarily new initiatives in nature, as adequate measures are already in use to tackle obesity or undernutrition separately. Nevertheless, these measures should be further pursued for DBM households.

Based on the findings stemming from the individual level that overweight/obesity is persisting while most underweight individuals do not remain so, the challenge is to improve the nutritional status of underweight individuals, while simultaneously tackling overweight and obesity. In other words, regarding undernutrition these findings suggest several courses of action to improve the individual's nutritional status while also preventing them from developing chronic and non-communicable conditions later. In addition, these research findings also point to the need to enhance the overweight or obese people's condition, i.e., helping them lose weight. Therefore, it is essential to consider all dimensions of the double burden, especially in DBM households that suffer from intra-household nutritional inequality with overweight and underweight individuals. Moreover, in households that transition from DBM to OVOB, most individuals become normal, which can be considered an improvement, while the others remain overweight or obese. However, it is likely that the previous underweight individuals, especially children, become overweight or obese ([Barker, 1990](#); [Edwards, 2017](#)). This is particularly problematic since once overweight or obesity is established, it persists both at the household and individual levels. Policy interventions that address undernutrition or overweight/obesity should thus be careful not to interfere with the other component of the DBM and instead provide coordinated nutrition action. Several proposals of double-duty actions are highlighted by [Hawkes et al. \(2020\)](#), including redesigning guidance for complementary feeding practices, redesigning school feeding programs, devising new nutritional guidelines for food in and around educational institutions, scaling up nutrition-sensitive agriculture programs, and designing new agricultural and food system policies. For example, in the case of a double burden household defined as an overweight or obese mother and an underweight child, while the mother will remain obese, the child will become normal. However, since the child was malnourished, she will be more likely to become obese in the future. Acting through double-duty actions such as maternal nutrition and antenatal care will, therefore, positively affect both the mother and the child.

Regarding the obesity aspect of the double burden, public actions must target individuals who may be at risk of becoming overweight or obese and those who suffer from persistent overweight or obesity. In terms of policies targeting the entire population, some have proven to be effective, such as the sugar-content-based tax called the Health Promotion Levy implemented in 2018, which has reduced sugary drink intake, mainly through reformulation and behavior change ([Essman et al., 2021](#)). Public policies and incentives such as the sugar tax must be maintained to limit unhealthy and ultra-processed foods, especially since DBM at the household level may be caused by the fact that individuals are eating ultra-processed foods. Reducing the consumption of ultra-processed foods can be done through fiscal policies and the labeling of unhealthy foods

(Reardon et al., 2021).

In South Africa, policies implemented to mitigate the obesity epidemic must be strengthened, especially for low-income households or minority groups. Our results show that households most affected by persistent OVOB are already experiencing socioeconomic inequalities: Africans, the economically inactive, the less educated, female-headed households, and those residing in rural areas. Therefore, public policies should focus on those households that are not directly targeted by the policies already implemented to mitigate the existing socioeconomic inequalities. Regarding agriculture, food systems, and food environments, a few main ideas are to promote interventions that can improve nutrition outcomes, promote diversity in food production, or include approaches to empower women in agricultural programs. The agricultural sector can play a crucial role in addressing the double burden of malnutrition by addressing inadequate access to nutrient-rich food, mainly through nutrition-sensitive agriculture (Ruel and Alderman, 2013). These measures are all the more critical since the COVID-19 pandemic is likely to increase the double burden. Indeed, changes in food choices, food shortages, lockdowns, mobility restrictions, and increased food insecurity are expected to make the situation much worse (Littlejohn and Finlay, 2021).

## 7 Conclusion

This paper studies the dynamics of two nutritional statuses at the household level: the DBM and OVOB in South Africa. Our findings can be summarized in four points. **First**, this study shows that the DBM is transitory within South African households. We find that a DBM household in  $t - 1$  has only between 9.52 and 14.85% chances of remaining so in  $t$ . These findings are robust to potential endogeneity issues, the use of robustness checks such as other anthropometric indicators, different household size, and the use of “raw” data. Our conclusions are consistent with the results of Roemling and Qaim (2013), who pointed out the DBM transitory nature at the household level. **Second**, we find that OVOB is a persistent status. The persistence rate is between 77.62 and 81.83%. As the persistence of OVOB at the household level has not yet been studied, this is quite a novel finding. **Third**, we find that DBM households in  $t - 1$  are more likely to be OVOB in  $t$ , rather than remaining in double burden in  $t$ . These findings are also consistent with Roemling and Qaim (2013). **Fourth**, these dynamics at the household level stem from individual level dynamics. The transition from DBM to OVOB is mainly explained by the fact that individuals who were underweight become normal, which can be considered a recovery from undernutrition and a general improvement. On the other hand, the persistence of OVOB at the household level is explained by a persistence at the individual level and overweight/obese individuals in DBM households remain so. Moreover, in the case of individuals with adverse nutrition in childhood, they may be more likely to become obese later on. It could imply a worsening of the obesity epidemic. These issues highlight the need to address multiple forms of malnutrition through

appropriate policies such as double-duty actions.

This study sets the stage for future research. Here, we considered the dynamics of the DBM at the household level analysis, which may seem surprising as one might think that an individual level model would make more sense in terms of human biology and behavioral science. However, the purpose of our paper was to examine the dynamics at the household level and then investigate the dynamics at the individual level to explore the implications. Therefore, the field of nutritional status study can also be extended to analyze deeply the dynamics of individual nutritional statuses in the framework of Markov chains. Likewise, one of the possible measures of the DBM is throughout the lifetime of individuals. Notwithstanding the time frame of our data does not allow us to measure DBM over an individual's lifetime, this deserves further study. In addition, we did not exhaustively examine the explanatory factors for the transition from DBM to OVOB and vice versa. This also requires further consideration.

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# Appendix

## Appendix A Correlations between BMI and WtHR

Table A.1: Correlation matrix between BMI and WtHR

	Pearson correlation coefficients		Spearman correlation coefficients	
	BMI	WtHR	BMI	WtHR
All waves				
BMI	1		1	
WtHR	0.753***	1	0.816***	1
Wave 1				
BMI	1		1	
WtHR	0.764***	1	0.818***	1
Wave 2				
BMI	1		1	
WtHR	0.528***	1	0.645***	1
Wave 3				
BMI	1		1	
WtHR	0.809***	1	0.820***	1
Wave 4				
BMI	1		1	
WtHR	0.878***	1	0.888***	1
Wave 5				
BMI	1		1	
WtHR	0.882***	1	0.896***	1

Notes: \*\*\*  $p < 0.01$

## Appendix B Variables used in the analysis

Table B.1: Definition of variables

Variable	Definition
DBM	DBM (Double Burden of Malnutrition) household: at least one overweight/obese individual ( $BMI \geq 25 \text{ kg/m}^2$ or $BMI\text{-for-age} > 1 \text{ SD}$ ) and one underweight individual ( $BMI < 18.5 \text{ kg/m}^2$ or $BMI\text{-for-age} < -2 \text{ SD}$ ) (1 = yes; 0 otherwise)
OVOB	OVOB (Overweight/Obese) household: at least one overweight or obese individual ( $BMI \geq 25 \text{ kg/m}^2$ or $BMI\text{-for-age} > 1 \text{ SD}$ ) and a varying number of normal individuals ( $18.5 \text{ kg/m}^2 \leq BMI < 25 \text{ kg/m}^2$ or $-2 \text{ SD} \leq BMI\text{-for-age} \leq 1 \text{ SD}$ ) (1 = yes; 0 otherwise)
<i>Socioeconomic variables</i>	
Expenditures	Monthly household expenditures (in logarithm)
Education of household head	Educational level of the household head (1 = no education; 2 = primary education; 3 = secondary education; 4 = higher education)
Employment of household head	Labor market status of the household head (1 = inactive; 2 = unemployed; 3 = employed)
<i>Additional variables</i>	
Urban	Household living area (0 = rural; 1 = urban)
Ethnic group of household head	Ethnic origin of household head (1 = African; 2 = Coloured ; 3 = Asian/Indian*; 4 = White)
Female head of household	Household head is a female (1 = yes; 0 otherwise)
Age of household head	Age of the household head (in years)
<i>Household composition</i>	
Household size	Number of individuals in the same dwelling
Entry	At least one entry of an individual in the household between two waves (birth or arrival) (1 = yes; 0 otherwise)
Exit	At least one exit of an individual in the household between two waves (death or exit) (1 = yes; 0 otherwise)
Number of children	Number of children in the household
Mean age of household	Sum of individuals' ages divided by the household size

Notes: \* The association of these two ethnic origins is derived from the NIDS surveys.

## Appendix C Additional robustness checks

Table C.1: Average marginal effects from the dynamic probit model, weight-for-height and BMI-for-age for children

	(1)	(2)
	DBM	OVOB
DBM in $t - 1$	0.040*** (0.012)	
OVOB in $t - 1$		0.096*** (0.014)
Explanatory variables ( $\bar{Z}_{it}$ )	Yes	Yes
Initial values ( $Z_{i0}$ )	Yes	Yes
Averages ( $\bar{Z}_t$ )	Yes	Yes
Observations	9,526	9,526
N. households	2,693	2,693
Log-likelihood	-2,755.459	-3,959.538
Wald chi2(42)	1,040.60	1,757.19
Prob > chi2	0.000	0.000

Notes: Standard deviations are in parentheses.

\*\*\*  $p < 0.01$  ; \*\*  $p < 0.05$  ; \*  $p < 0.1$ .

Table C.2: Predicted probabilities, weight-for-height and BMI-for-age for children

Nutritional status	Dynamics			
	Entry	Persistence	Exit	Mean duration
DBM	10.79	14.67	85.33	1.17
OVOB	68.79	78.56	21.44	4.66

Notes: Probabilities can be interpreted as entry, persistence and exit rates:  $Pr(1|0)$  ;  $Pr(1|1)$  ;  $Pr(0|1)$ . Mean duration:  $1/Pr(0|1)$ .

Table C.3: Average marginal effects from the dynamic probit model, raw data

	(1)	(2)
	DBM	OVOB
DBM in $t - 1$	0.025** (0.012)	
OVOB in $t - 1$		0.074*** (0.014)
Explanatory variables ( $\bar{Z}_{it}$ )	Yes	Yes
Initial values ( $Z_{i0}$ )	Yes	Yes
Averages ( $\bar{Z}_t$ )	Yes	Yes
Observations	8,780	8,780
N. households	2,612	2,612
Log-likelihood	-2,612.702	-3,854.904
Wald chi2(42)	849.48	1,414.00
Prob > chi2	0.000	0.000

Notes: Standard deviations are in parentheses.

\*\*\*  $p < 0.01$  ; \*\*  $p < 0.05$  ; \*  $p < 0.1$ .

Table C.4: Predicted probabilities, raw data

Nutritional status	Dynamics			
	Entry	Persistence	Exit	Mean duration
DBM	10.75	13.14	86.86	1.15
OVOB	70.06	77.62	22.38	4.47

Notes: Probabilities can be interpreted as entry, persistence and exit rates:  $Pr(1|0)$  ;  $Pr(1|1)$  ;  $Pr(0|1)$ . Mean duration:  $1/Pr(0|1)$ .