Nowcasting multidimensional poverty in the occupied Palestinian territory

UNITED NATIONS
الاسكوا
ESCWA

Shared Prosperity Dignified Life

UNITED NATIONS
الاسكوا
ESCWA

Shared Prosperity **Dignified Life**

VISION
ESCWA, an innovative catalyst for a stable, just and flourishing Arab region

MISSION
Committed to the 2030 Agenda, ESCWA's passionate team produces innovative knowledge, fosters regional consensus and delivers transformational policy advice. Together, we work for a sustainable future for all.

E/ESCWA/CL3.SEP/2021/TP.7

Economic and Social Commission for Western Asia

Nowcasting multidimensional poverty in the occupied Palestinian territory

United Nations
Beirut

Paul Makdissi
Department of Economics, University of Ottawa
Email: paul.makdissi@uottawa.ca

United Nations publication issued by ESCWA, United Nations House,
Riad El Solh Square, P.O. Box: 11-8575, Beirut, Lebanon.

Website: www.unescwa.org.

21-00388

Acknowledgments

The author would like to thank the following ESCWA staff members for their valuable input and assistance with the data: Rima Abdul Khalek, Jawad Al-Saleh, Rabih Bashour, Sama El Hage Sleiman, Vladimír Hlásny, Marwan Khawaja, Nathan Reece, and Myra Yazbeck.

Contents

Introduction

Studying inequality and poverty in the Arab region is a challenging task. As pointed out in Atamanov and others (2020), the Arab region has insufficient statistical capacity. Few countries survey their population on income and expenditure. In Arab countries that run these types of surveys, statistical offices perform this exercise irregularly. In this context, analysts have to find alternative approaches to assess inequality and poverty in the region. One alternative approach is to look at multidimensional poverty in a multinational poverty index (MPI) framework (Alkire and Santos, 2014; Alkire and Foster, 2011). This approach relies on the type of data the analyst usually finds in the demographic health surveys. ESCWA and others (2020) has adopted the approach to the Arab region's specificity. Following the standard approach of building such an index, ESCWA chose the dimensions and indicators to reflect the development goals of the Arab region. Unfortunately, because demographic health surveys do not include information on household income or expenditure, the Arab multidimensional poverty index does not include a monetary poverty dimension.

Since better data is available for the State of Palestine, Khawaja, Al-Saleh, Reece and Conconi (2020) propose a context-specific Palestinian multidimensional poverty index. The proposed index's dimensions and indicators include a monetary dimension and information on security and freedom, which are essential considerations in the Palestinian context. The choice of dimensions and indicators builds on the Palestinian basic law and Palestinian child protection and labour laws. Khawaja and others (2020) build the Palestinian multidimensional poverty index using the last version of the Palestinian Consumption and Expenditure survey (PECS) of 2016. The previous version of the same survey dates of 2011. Besides, the PECS 2011 does not include all indicators used in the Palestinian multidimensional poverty index. The presence of such data limitation points to the need to nowcast these poverty indices between two non-consecutive surveys and forecasting beyond the last survey.

Despite their strong assumptions, nowcasting and forecasting approaches to computing poverty indices remain an essential exercise from a policy perspective. Even if there is uncertainty on the exact magnitude of the index, capturing at least the direction of change is essential for the design of evidence-based policies. Some papers, such as Klassen and Lange (2012), proposed models to nowcast deprivation in specific dimensions such as health. However, until very recently, the literature was still silent on proposing models to nowcast multidimensional poverty except for a forthcoming paper (Ram, 2020), an OPHI working paper (Alkire, Nogales, Quinn and Suppa, 2020), and an ESCWA technical report (Makdissi, 2020).

The present report aims to contribute to this modelling exercise for nowcasting the Palestinian multidimensional poverty index. Our approach is related to Makdissi (2020) because it proposes a dynamic modelling approach of multidimensional poverty that separately models each indicator's change. This analytical choice allows for more flexibility on the modelling assumptions made to estimate the counterfactual change in each indicator's univariate distribution. In addition to Makdissi (2020), we propose solutions in a context where the indicators are not available in two consecutive surveys. The present paper's modelling approach considers political and security factors that may influence the dynamics of some of the indicators more than chronology and change in economic conditions. This modelling approach is handy in a context of a multidimensional poverty index that includes dimensions such as individual freedoms and security.

Another contribution is the Palestinian State model disaggregation into Gaza and West Bank regions and modelling them separately. This exercise is essential since the two regions are physically separated and have different experiences in terms of occupation type. The number of observations in Gaza being relatively low, the simulations at the regional level are less reliable, even within the theoretical model framework. Nevertheless, the simulation results' point estimates indicate that multidimensional poverty sometimes moves in opposite directions in both regions. In particular, the relative stability of multidimensional poverty in 2020 compared to 2019 at the state-wide level results from an increase in the West Bank's multidimensional poverty and a reduction of multidimensional poverty in Gaza during the pandemic. This difference is essentially due to a substantial decrease in Gaza injuries in 2020 and 2021. The reduction in the number of injuries in the West Bank was smaller than the one in Gaza. Besides, there was an increase in the number of demolitions in the West Bank in 2020 and early 2021.

1. A theoretical model of multidimensional poverty in the State of Palestine

The first step in constructing the Palestinian multidimensional poverty index consists of assigning a score to each household in the data set. This score aggregates the information on twenty-two indicators (grouped in seven dimensions) of the household's wellbeing. For each deprived indicator for the household, the analyst adds a factor to the household's score. Table 1 displays a detailed description of the Palestinian multidimensional poverty index's different indicators and their corresponding deprivation cutoffs. Note that the indicators are negative attributes. Since we aim to model each indicator's distribution as a distribution of individual attributes in wellbeing, those ill-fare indicators are inverted and interpreted as the absence of this same indicator. Also, our modelling approach uses the complete underlying distribution of the two non-binary indicators – educational attainment and consumption expenditures. For educational attainment, we use the complete marginal distribution of the household's maximum educational attainment. We use a poverty cutoff at 12 years of schooling, which corresponds to high school completion. For expenditures, we follow the definition of monetary poverty of the Palestinian Central Bureau of Statistics (PCBS). We use the complete distribution of the household equivalent total expenditures in shekels of 2016 and use a poverty line of 776 shekels per month. We construct the household's equivalent expenditure using the PCBS's equivalence scale.

(1) $$m(n_a, n_c) = [n_a + 0.46n_c]^{0.89}.$$

where n_a and n_c represent respectively the number of adults and children in the household.

Table 1. Dimensions and indicators of the Palestinian multidimensional poverty index

Dimension of Poverty	Indicator	Deprived if--	Indicator's weight
Education	School enrolment	Household has any child aged 6-17 not enrolled in school (not including those who graduated secondary school)	$d_1 = 1/30$
	Repetition	Household has any child aged 7-18 ever enrolled in school and repeated a school year, OR Household has any has any child aged 7-18 never been enrolled	$d_1 = 1/30$

Dimension of Poverty	Indicator	Deprived if--	Indicator's weight
	Educational attainment – persons aged 19-50	All household members aged 19-50 not completing secondary school	$d_1 = 1/30$
	Quality of education – household with children age 6-17 years enrolled in school	Household has any child aged 6-17 who had problems with education quality. Indicated a serious problem with the school in terms of poor teaching or lack of teachers or lack of books or lack of facilities.	$d_1 = 1/30$
Health	Disability	Any household member having great difficulty in hearing, vision, movement, communication, OR understanding	$d_1 = 1/30$
	Chronic disease	All household members aged 30+ suffering from a diagnosed chronic disease.	$d_1 = 1/30$
	Health insurance	Household lacking health insurance: (the head OR any member has health insurance defined as NOT deprived)	$d_1 = 1/30$
	Health Access	Household lives more than 5 km away from the nearest doctor clinic or hospital	$d_1 = 1/30$
Employment	Unemployment	None of adults aged 18+ currently employed	$d_1 = 1/30$
	Employment benefits	Wage earners aged 15-60 lacking paid sick leave, maternity leave or annual vacation	$d_1 = 1/30$
	Quality of work	Household has any working member 18+ who is currently an irregular wage employee, OR does not have a contract OR is a seasonal & causal worker OR has worked only 6 months during last 12 months.	$d_1 = 1/30$
	Youth NEET	Household has any youth aged 18-24 who is not in school or training and unemployed	$d_1 = 1/30$
Housing conditions and access to services	Access to piped water	Dwelling is not connected to public network	$d_1 = 1/30$
	frequency of water and electricity supply	Disruption of water supply (daily) during the past year	$d_1 = 1/30$

Dimension of Poverty	Indicator	Deprived if--	Indicator's weight
	Ventilation problems in dwelling	Dwelling suffers from noise, smoke or any other pollutant	$d_1 = 1/30$
	Overcrowding	More than 3 persons per sleeping room	$d_1 = 1/30$
Safety and use of assets	Theft or damage to property	Stealing from household or damage of household property as a result of attacks last year	$d_1 = 2/45$
	Ownership and use of assets	Household lost land, house/building or business establishment during the past year due to confiscation or demolition Household was unable to use agricultural land or private property due to restrictions of movement	$d_1 = 2/45$
	Interpersonal and state violence	Any household member attacked or forcibly assaulted with or without a weapon last year OR, any child or women hit or attacked by another family member during the past year. OR Injuries, deaths or torture in household from state/settler violence during the past year	$d_1 = 2/45$
Personal freedom	Freedom of movement	A household member was not able to visit family, relatives, or friends because of checkpoints, wall or travel restrictions during the past year	$d_1 = 1/15$
	Control of women's income or women's participation in the labour market	Any women in household who does not have a separate bank account or does not control her use of income or earnings OR Any women in household does not work (or look for work) because of husband/father/brother's restrictions	$d_1 = 1/15$ $d_1 = 1/15$
Monetary resources	National poverty line	Household is below the national poverty line	$d_1 = 1/5$

Source: Khawaja, Al-Saleh, Reece and Conconi, 2020.

There are two steps in the computation of the multidimensional poverty index. In a first step, a deprivation cutoff, z_k, is chosen for each indicator $k \in \{1,2,\dots,22\}$. Then, for each household $i \in \{1,2,\dots,n\}$, a score is assigned based on the indicators $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{i22})$ associated with this household. This score, s_i is given by:

(2) $$s_i = \sum_{k=1}^{22} \mathbf{1}\,(x_{ik} \leq z_k) \times d_k.$$

where d_k represents the weight assigned to indicator k, $\sum_{k=1}^{22} d_k = 1$ and $\mathbf{1}(\cdot)$ is an indicator function that takes a value of 1 if the argument is true and a value of 0 if it is false.

A second step consists of identifying multidimensional poverty by choosing a cutoff, $c \in (0,1)$. This cutoff is fixed at 0.20 for the Palestinian multidimensional poverty index. A household is poor if its score is larger or equal to this cutoff. Note that in the empirical section, we will test the sensitivity of the results on this poverty cutoff's choice. The multidimensional poverty headcount is then given by:

(3) $$MPH = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}\,(s_i \geq c).$$

The Palestinian multidimensional poverty index is:

(4) $$MPI = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}\,(s_i \geq c) \times s_i.$$

It is straightforward to perform the above exercise for each year for which a survey is available. However, these surveys are not available every year. In this context, one needs to model these two indices' value for the years without a survey. The rest of this section sets out the modelling approach proposed by Makdissi (2020) that we will adapt and use in the present paper.

One can think of the multidimensional poverty headcount and the Palestinian multidimensional poverty index at year t as two functionals of the multidimensional cumulative distribution of indicators, $H_t(\mathbf{x})$, of that year. This multidimensional cumulative distribution function is formally defined as

(5) $$H_t(\mathbf{x}) = H_t(x_1, x_2, \dots, x_{22}) = \Pr[X_1 \leq x_1, X_2 \leq x_2, \dots, X_{22} \leq x_{22} | \text{year } = t].$$

Proposing a model of $H_t(\mathbf{x})$ would allow to nowcast or forecast these two indices $MPH_t = MPH\big(H_t(\mathbf{x})\big)$ and $MPI_t = MPI\big(H_t(\mathbf{x})\big)$.

In order to estimate counterfactuals of the multidimensional cumulative distributions $H_t^G(\mathbf{x})$ for the years in which we do not have a survey, Makdissi (2020) propose to follow an insight of Khaled, Makdissi, Rao, and Yazbeck (2020) and build on Sklar's Theorem1 that stipulates that $H_t^G(\mathbf{x})$ can be expressed as:

(6) $$H_t^G(\mathbf{x}) = C_t^G\left(F_{X_1,t}(x_1), \dots, F_{X_{22},t}(x_{22})\right).$$

i.e. in terms of a 22-dimensional copula $C(\cdot)$ and the univariate marginal distribution functions $F_{X_k,t}(x_k)$, $k \in \{1,2,\dots,22\}$. One can generally also recover $H_t^G(\mathbf{x})$ from the copula $C_t^G(\cdot)$ and the marginal distribution functions $F_{X_k,t}(x_k)$, $k \in \{1,2,\dots,22\}$. The main analytical advantage of looking at the problem with a copula approach is that it allows for the modelling of each one of the indicators $k \in \{1,2,\dots,22\}$ separately and the reconstruction of a counterfactual multidimensional cumulative distribution $H_t^G(\mathbf{x})$ from the counterfactuals of each indicator. The

1 For more information on Sklar's Theorem, see Hofert, Kojadinovic, Mächler and Yan (2018).

only assumption that one needs in this context is the stability of the copula.

In our context, since we have some discrete indicators, the copula function is not unique. Some solutions in the statistical literature analyse situations in which some dimensions are discrete and others continuous. These solutions consist of choosing one of the potential copulas that fit the data. In order to account for survey weights, we follow Makdissi (2020) and adapt the checkerboard copula estimator from Genest, Nešlehová, and Rémillard (2017)[2] using a Hájek weighted estimator (annex 1 gives the details of the estimation procedure). The model's construction implies estimating each indicator's cumulative distribution function and the copula for the reference year. We can then use this model to build counterfactuals of the joint distribution and indices when one or more indicators change following a simulated pattern or an assumed exogenous shock.

This approach allows us to decompose the change between two observational years as induced by a change in marginal distributions and a change in the copula. For instance, let $H^G_{t_1:t_0}(\mathbf{x})$ represent the multidimensional cumulative distribution function as the copula function of year t_0, $C^G_{t_0}(\cdot)$, and the marginal distribution of year t_1, $F^G_{X_k,t_1}(x_k)$, $k \in \{1,2,\ldots,22\}$. Using this notation, a change in the Palestinian MPI for group between any year t and 2016 can be rewritten as:

(7) $$MPI\left(H^G_{2016}(\mathbf{x})\right) - MPI\left(H^G_t(\mathbf{x})\right) = MPI\left(H^G_{2016:2016}(\mathbf{x})\right) - MPI\left(H^G_{t:2016}(\mathbf{x})\right) + MPI\left(H^G_{t:2016}(\mathbf{x})\right) - MPI\left(H^G_{t:t}(\mathbf{x})\right).$$

where:

(8) $$MPI\left(H^G_{2016:2016}(\mathbf{x})\right) - MPI\left(H^G_{t:2016}(\mathbf{x})\right) = \Delta MPI \text{ assuming copula stability.}$$

and

$$MPI\left(H^G_{t:2016}(\mathbf{x})\right) - MPI\left(H^G_{t:t}(\mathbf{x})\right) = \Delta MPI \text{ induced by change in the copula.}$$

Assuming stability of the copula allows us to estimate the indices associated with equation (8). If we have models for each univariate marginal distribution, we can estimate the change corresponding to equation (8).

Let $\mathcal{D}$ indicate the 22-dimensional domain of integration. The terms on the r.h.s. of equation (8) can be evaluated using the expressions:

(9) $$MPH\left(H^G_{t:2016}(\mathbf{x})\right) = \int_{\mathcal{D}} \mathbf{1}\left(\sum_{k=1}^{22} d_k\, \mathbf{1}(x_k \leq z_k) \geq c\right) \mathrm{d}H^G_{t:2016}(\mathbf{x}).$$

(10) $$MPI\left(H^G_{t:2016}(\mathbf{x})\right) = \int_{\mathcal{D}} \left[\mathbf{1}\left(\sum_{k=1}^{22} d_k\, \mathbf{1}(x_k \leq z_k) \geq c\right) \times \left(\sum_{k=1}^{22} d_k\, \mathbf{1}(x_k \leq z_k)\right)\right] \mathrm{d}H^G_{t:2016}(\mathbf{x}).$$

These multiple integrals can be evaluated using Monte Carlo integration (technical details are in annex 2).

2 Smith and Khaled (2012) propose another type of solution: a Bayesian latent approach to model the discrete dimensions.

2. Modelling the change of the 22 indicators in the State of Palestine

For our empirical analysis, we use the Palestinian Consumption and Expenditure survey (PECS) of 2011 and 2016. Twelve of the twenty-two indicators in table 1 are available in both surveys. The remaining ten indicators are only available in 2016. Inspection of equations (9) and (10) and the details of the Monte Carlo integration in annex 2 indicate that the only dynamic we need to estimate the counterfactual indices is a model of the change in the incidence of the deprivation in each dimension $F^M_{X_k,t}(z_k)$. The estimated copula produces the remaining structure of the index.

As shown in Makdissi (2020), for the context of Iraq, using the estimated copula of a year to model the multidimensional poverty index of another year under the stability of the copula assumption produces numbers that are close to the estimated numbers if one uses the correct marginal distributions of each deprivation indicator. In other words, the model produces a counterfactual multidimensional poverty index that is as good as the counterfactual projection in each dimension.

Since $F^M_{X_k,t}(z_k) \in [0,1]$, we propose to calibrate the dynamic of $F^M_{X_k,t}(z_k)$ for the twelve indicators for which we have two years of observations on a two-parameter logistic function:

(11) $$F^M_{X_k}(z_k) = \frac{1}{1+e^{-\alpha_k+\beta_k y_t}}.$$

where y_t is the value of an index at year t. Depending on the indicator, this index may be time, per capita state-wide (regional) production, or one of the political indices: the demolition index, or the occupation severity index. The state-wide and regional real per capita GDP from 2011 to 2019 are obtained from the PCBS.[3] It is important to note that these estimates exclude the parts of Jerusalem governorate which were annexed by Israel in 1967. The values for 2020 and 2021 are obtained by applying the growth projections for 2020 and 2021 produced in the World Bank economic update for West Bank and Gaza in October 2020.[4] We construct the political indices using information from the Country Office in the occupied Palestinian territory (oPt) of the United Nations Office for the Coordination of Humanitarian Affairs (OCHA). The demolition index is just the number of demolitions in the year[5] divided by the annual number of demolitions' geometric average during the period of analysis. We use this index for the state-wide projections and the West Bank's regional projection since demolitions due to colonization is a West Bank-specific phenomenon. At the state-wide level, the occupation severity index is a weighted

3 www.pcbs.gov.ps/Portals/_Rainbow/Documents/E_Na_accounts_2014_2015_constant.html.

4 www.worldbank.org/en/country/westbankandgaza/publication/economic-update-october-2020.

5 www.ochaopt.org/data/demolition.

geometric average of the demolition index (0.70) and an index of the number of Palestinian injuries (0.30) due to conflict.[6] This index is the ratio of yearly injuries to the geometric average of injuries during the period of analysis. For the West Bank regional occupation severity index, we use a similar index but using only the West Bank's injuries to construct the index of annual injuries.

For Gaza, we need to substitute the demolition index by another index capturing the specificity of Gaza's occupation compared to the West Bank. Israel has imposed a blockade on Gaza since 2007. To capture variation in this blockade's intensity, we pick the quantity of an essential non-food item entering the Strip: hygiene and cleaning supply. We use the information on the number of truckloads of hygiene and cleaning supply[7] and Gaza's estimated population[8] to get an estimate of the number of truckloads per 100,000 habitants. We then construct the index as the ratio number, the geometric average of the number of truckloads per 100,000 habitants per year for analysis to the annual number of truckloads for the year of interest.

For the ten indicators for which we have only one year of observations, we can only calibrate one of the above logistic parameters. To fully identify the dynamics of these indicators, we will assume that the semi-elasticity (β_k) of the odds-ratio $F^M_{X_k,t}(z_k)/(1 - F^M_{X_k,t}(z_k))$ is equal to the same semi-elasticity for a close enough indicator for which we have two years of observations and for which dynamics is linked with the same index.

We have a vector of 33 parameters to calibrate to capture our simple model of the 22 univariate marginal distributions' dynamics. Let Ω represents the vector of these 34 calibrated parameters. We follow an insight from Abdelkhalek and Dufour (1998, 2006) and Dufour, Kichian and Khalaf (2013) and assume that the vector of parameters to be calibrated is a function of many stochastic variables. In other words, $\Omega = \omega(\mathbf{X}_{2011}, \mathbf{X}_{2016})$, a function of the fourteen stochastic indicators in 2011 and 2016 and the ten additional ones appearing only in the 2016 wave of the survey. To account for sampling variability, we recalibrate this vector at each bootstrap iteration.

A. Baseline modelling framework

The baseline modelling framework will produce simulations for all years between 2011 and 2021. Since the only years for which we have a survey of all the indicators is 2016, the simulated model indices will be compared with the estimated indices for that year.

The following indicators for which we have two years of observation will be linked with the index of per capita state-wide (regional) production (below, we give our wellbeing definition of the ill-being indicators):

(1) X_1: All children aged 6-17 enrolled in school.

---

6 www.ochaopt.org/data/casualties.

7 www.ochaopt.org/data/crossings.

8 These estimates can be found at www.pcbs.gov.ps/Portals/_Rainbow/Documents/%D8%A7%D9%84%D9%85%D8%AD%D8%A7%D9%81%D8%B8%D8%A7%D8%AA%20%D8%A7%D9%86%D8%AC%D9%84%D9%8A%D8%B2%D9%8A%2097-2017.html.

(2) X_2: All children aged 6-17 enrolled in school and never repeated a school year.

(3) X_7: Health insurance coverage.

(4) X_9: At least one adult in the household is employed.

(5) X_{10}: Workers in the household have paid benefits.

(6) X_{11}: All workers in the household in regular jobs.

(7) X_{12}: All youth in school, training or employment.

(8) X_{22}: Equivalent total consumption.

We assume that "X_4: No problem of quality of education" has the same semi-elasticity of the odds-ratio as X_2.

The following indicators for which we have two years of observation will be linked with the index of time:

(1) X_3: Maximum schooling in the household.

(2) X_{13}: Connected to public piped water network.

In addition, the following indicators that are linked with the demolition index will be linked with time for the regional Gaza simulations:

(1) X_8: Household lives less than 5 km away from the nearest doctor clinic or hospital.

(2) X_{15}: No ventilation, smoke, pollutant issues.

(3) X_{16}: Not overcrowded housing.

We assume that "X_5: No disability in the household" has the same semi-elasticity of the odds-ratio as X_8 and that "X_{14}: No disruption of piped water or electricity" has the same semi-elasticity of the odds-ratio as X_{16}.

The following indicator for which we have two years of observation will be linked with the index of severity of occupation:

(1) X_{18}: Full access to property and no confiscation.

In addition, the following indicators will be assumed to have the same semi-elasticity of the odds-ratio as X_{18}:

(1) X_{17}: No theft or damage to property.

(2) X_{19}: Not subject to interpersonal or state violence.

(3) X_{20}: Full freedom of movement.

(4) X_{21}: Women are empowered.

Finally, the indicator "X_6: At least one member does not have chronic disease" is assumed constant over time except for the impact of the COVID-19 pandemic to be described below.

B. Modelling the impact of the COVID-19 pandemic

By its impact on the international economy, the COVID-19 pandemic has impacts that are channelled through the induced change in aggregate production. The baseline model already captures these impacts since in its October 2020 economic update on the West Bank and Gaza, the World Bank estimated that in 2020 there will be a contraction of 8 per cent of GDP and that only a 2.5 per cent recovery is predicted for 2021. These assumptions are included in our model, and the baseline simulation results will capture these impacts of COVID-19.

In addition to these impacts that are channelled through economic variables, we can expect additional impacts. Some minor or transitory diseases (including COVID-19 infections) may become chronic conditions because of a lack of appropriate treatment. This lack of treatment may be the consequence of hospital unavailability due to COVID-19 pressure on the health system or the lack of money and/or lack of health insurance. For this reason, we assume that the COVID-19 pandemic has a small impact of 2 per cent on chronic disease.

The COVID-19 pandemic impacts three of our education indicators through the state-wide production channel. One of the containment policy responses to the COVID-19 pandemic consists of closing schools. In December 2020, UNICEF reported that 170 schools have temporarily closed in the occupied Palestinian territory in the first few months of the 2020-2021 academic years following health protocols because of confirmed COVID-19 cases among pupils or school staff.[9] These affected schools represent around 7.5 per cent of total schools in the State of Palestine. Because these events typically have a higher impact on poor households, we assume the following additional impacts on education indicators: an additional 8 per cent on school enrolment, an additional 6 per cent on repetitions, and an additional 20 per cent on the quality of education. School closures may also affect the graduation rates of the present cohort. Based on the 2021 modelling of the Palestinian population produced by the International Data Base of the US Census Bureau, teenagers from 15 to 19 in the West Bank and Gaza represent 10.5 per cent and 12.1 per cent of the respective population of these two regions.[10] School closure may substantially impact the dropout rates of the present cohort. Given their relative share of the total population, we assume a small impact of 2 per cent on the overall population's educational attainment. These modelled impacts are conservative estimates for the actual unobserved impacts through various channels.

[9]~www.unicef.org/sop/stories/making-schools-safe-state-palestine-amidst-widening-pandemic.

[10]~www.census.gov/programs-surveys/international-programs/about/idb.html.

3. Simulation results

The present section presents the results of the modelling approach described in sections I and II. In addition to time, our indicators' dynamics are linked with indices of per capita state-wide (regional) production, demolition indices, and severity of occupation indices presented in the previous section. Table 2 present the values of per capita production and the numbers of demolitions, days of closure of the Rafah crossing, and injuries. Table 2b presents the value of the indices based on these numbers.

Two crucial differences between Gaza and the West Bank are worth mentioning. Although per capita production increases between 2011 and 2016 in the West Bank, Gaza's per capita production decreased by 16.2. per cent in 2014 and another 1.4 per cent in 2015 due to war in Gaza in 2014 and the Israeli blockade imposed since 2007. Also, the severity of occupation indices for the two regions moved in opposite direction year per year during the 2015 to 2021 period.

Table 2a. Information on GDP, demolitions, truckloads of hygiene and cleaning supply and injuries

	Year	Per Capita Real GDP (USD of 2015)	Demolitions (West Bank) and number of truckloads of hygiene and cleaning supply per 100,000 habitants (Gaza)	Number of injuries
Statewide level	2011	3,163.60	631	2,135
	2012	3,242.10	623	4,668
	2013	3,314.50	663	3,992
	2014	3,233.00	609	17516
	2015	3,277.90	560	14,632
	2016	3,489.80	1,094	3,459
	2017	3,463.10	419	8,443
	2018	3,417.70	460	31,254
	2019	3,378.30	623	15,460
	2020	3,108.04*	848	2,750
	2021	3,185.74*	1,380**	1,398***
West Bank	2011	4,062.70	631	1,660

	Year	Per Capita Real GDP (USD of 2015)	Demolitions (West Bank) and number of truckloads of hygiene and cleaning supply per 100,000 habitants (Gaza)	Number of injuries
	2012	4,195.00	623	3,185
	2013	4,262.30	663	3,904
	2014	4,358.70	609	6,034
	2015	4,460.80	560	13,230
	2016	4,761.10	1,094	3,249
	2017	4,851,00	419	7,238
	2018	4,854.40	460	6,077
	2019	4,822.50	623	3,592
	2020	4,436.70*	848	2,694
	2021	4,547.62*	1,380**	1,386***
Gaza	2011	1,788.70	104.78	475
	2012	1,880.30	108.48	1,492
	2013	1,971.50	88.29	88
	2014	1,651.30	90.05	11,482
	2015	1,628.90	64.65	1,402
	2016	1,730.80	86.24	210
	2017	1,556.60	79.82	1,205
	2018	1,458.30	113.82	25,177
	2019	1,422.20	117.05	11,898
	2020	1,308.42*	83.30	56
	2021	1,341.13*	74.05****	12***

Sources: PCBS and OCHA oPt data.

Note: (*) Per capita GDP values for 2020 and 2021 are based on the projection of produced in the World Bank economic update for West Bank and Gaza in October 2020. (**) Projection based on demolition during January and February 2021. (***) Projection based on injuries of January and February 2021. (****) Projection based on truckloads in January and February 2021.

Table 2b. State-wide production, demolition and occupation severity indices

	Year	State-wide (Regional) production index	Demolition index	Occupation severity index
State-wide level	2011	100.00	93.22	69.03
	2012	103.53	92.04	86.51
	2013	105.84	97.95	86.22
	2014	103.23	89.97	126.60
	2015	104.67	82.73	113.11
	2016	111.44	161.63	117.27
	2017	110.59	61.90	78.29
	2018	109.14	67.96	123.76
	2019	107.88	92.04	123.96
	2020	99.25	125.28	91.59
	2021	101.73	203.88	105.13
West Bank	2011	100.00	93.22	73.70
	2012	103.26	92.04	88.81
	2013	104.91	97.95	98.61
	2014	107.29	89.97	105.88
	2015	109.80	82.73	126.35
	2016	117.19	161.63	132.50
	2017	119.40	61.90	86.06
	2018	119.49	67.96	87.18
	2019	118.70	92.04	92.07
	2020	109.21	125.28	104.81
	2021	111.94	203.88	120.73
Gaza Strip	2011	100.00	-	83.52
	2012	105.12	-	90.77
	2013	110.22	-	82.33
	2014	92.32	-	131.63
	2015	91.07	-	143.74
	2016	96.76	-	91.72
	2017	87.02	-	117.11
	2018	81.53	-	115.32

	Year	State-wide (Regional) production index	Demolition index	Occupation severity index
	2019	79.51	-	104.33
	2020	73.15	-	82.91
	2021	74.98	-	79.02

Sources: ESCWA calculations based on PCBS and OCHA oPt data.

Note: Values for 2021 are based on observation in January or January and February and are annualized. Also note that these indices are relative and region-specific. They are not comparable between regions and are just comparable from one year to the other in the same region. The value of the demolition index at year t_0 is given by

$$I_{Dt_0} = \frac{n_{Dt_0}}{\prod_{t=1}^{11} n_{Dt}^{1/11}}.$$

where n_{Dt} is the number of demolitions in year t. For the occupation severity index, we first construct injuries index, I_{It_0} similar to the demolition index. For Gaza, we first construct a truckload index which is given by:

$$I_{Tt_0} = \frac{\prod_{t=1}^{11} n_{Tt}^{1/11}}{n_{Tt_0}}.$$

where n_{Tt} is the number of truckloads of hygiene and cleaning supply per 100,000 habitants in year t.

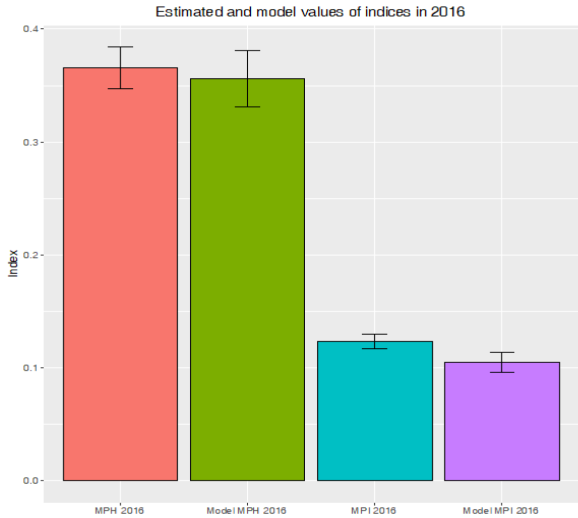
The overall and West Bank occupation severity index for year t_0 is given by: $I_{Ot_0} = e^{0.7\,ln(I_{Dt_0})+0.3\,ln(I_{It_0})}$.

For Gaza, it is: $I_{Ot_0} = e^{0.9\,ln(I_{Tt_0})+0.1\,ln(I_{It_0})}$.

Figure 1 presents the estimated multidimensional poverty headcount and Palestinian multidimensional poverty index using the 2016 data. The figure compares the estimated results with the results produced by the model. Although the points estimates are not identical, they fall within the 95 per cent confidence intervals range.

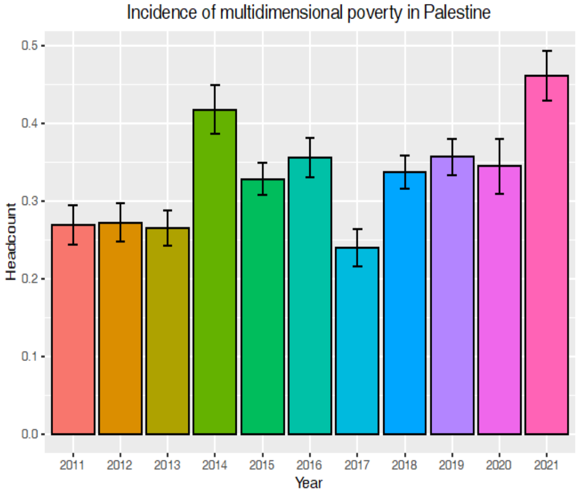
Figure 2 presents the dynamics of the multidimensional poverty headcount produced by the model. The result indicates that compared to 2019, there would be a slight reduction in the average simulated value of the multidimensional poverty headcount. However, if we consider the 95 per cent confidence interval of the simulated values, the values for 2020 cannot be distinguished from those of 2019. Figure 3 presents the dynamics of the Palestinian multidimensional poverty index. The dynamics in 2020 and 2021 are similar to the headcount dynamics except that there is a slight increase of the average value of the multidimensional poverty index simulations for 2020 compared to 2019, but as for the headcount, the change from 2019 is not significant.

Figure 1. Model versus estimated values of the indices in 2016



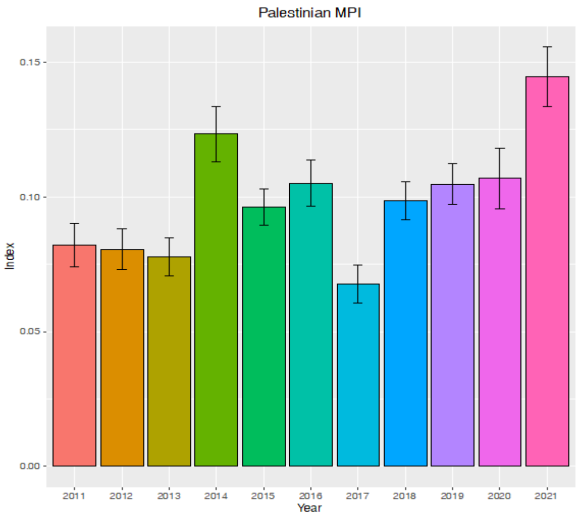
Sources: ESCWA calculations based on PCBS and OCHA oPt data.

Figure 2. Multidimensional poverty headcount trends



Sources: ESCWA calculations based on PCBS and OCHA oPt data.

Figure 3. Palestinian multidimensional poverty index trends

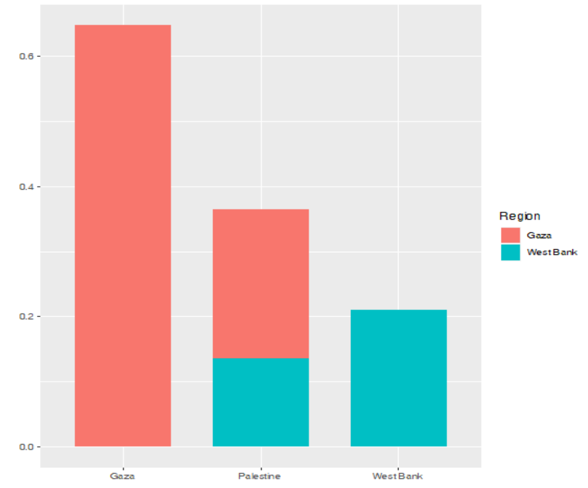


Sources: ESCWA calculations based on PCBS and OCHA oPt data.

The results for 2020 may seem surprising in the presence of COVID-19. However, the result for 2021 seems to be more intuitive and indicates a rise of the simulated values under COVID-19 shocks. One needs to look into the indices' values in Table 2b which are driving the dynamics of the model. If we compare the severity of occupation indices for 2020 with these of 2019, there is a significant reduction of this index at the state-wide level. Looking at the regional breakdown, these results seem to be driven by the relative reduction of Gaza's severity. Although Gaza represents 35.6 per cent of the total population represented by the 2016 data, as illustrated by figure 4, it contributes to 63.0 per cent of the total number of poor households in the Palestinian population represented in the 2016 data set. Since the model is calibrated using the copula of 2016, Gaza changes will impact the overall dynamics more than its relative share of total population.

The significant rise of demolition activities in the West Bank in early 2021 counterbalances the reduction of injuries in the West Bank and Gaza. In this context, the impact of COVID-19 compounds with these changes in political factors and generates simulated levels of poverty comparable with the one obtained from the simulation of 2014 during the war in Gaza. All these simulated facts indicate that for the State of Palestine, political and security factors seem to be as important as the impact of a global pandemic on multidimensional poverty.

Figure 4. Regional contributions to the multidimensional poverty headcount



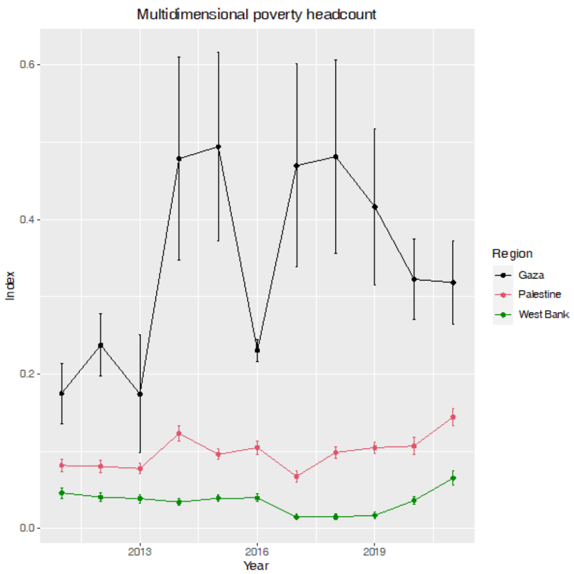
Sources: ESCWA calculations based on PCBS and OCHA oPt data.

The significant differences between Gaza's underlying economic and political factors and the West Bank depicted in Table 2b, highlight the difference in per capita production growth and the severity of occupation trends. As the two regions have faced different Israeli policies and practices, the divergence rate has substantially increased since 2005. In September 2005, Israel unilaterally "disengaged" from Gaza. Nevertheless, according to various United Nations bodies and resolutions, Gaza remains an occupied territory, namely due to Israel’s control of its airspace, its territorial waters, and most of its land crossings. In 2007, Israel imposed a near-total blockade on the Gaza Strip, severely restricting people and goods' movement in and out of the Strip. The blockade had a detrimental social and economic impact on Gaza. This was compounded by a series of military offensives, the most intense of which was in July-August 2014, that decimated the Strips infrastructure.

At the same time, Israel escalated its land grab policies and cementing its control over Palestinian territory and resources. These policies include mobility restrictions within the West Bank, population displacement, and hindering social and economic activity. They also included increased investment and acceleration of illegal settlement activity in the West Bank and constructing a wall that de facto annexes around 10 per cent of West Bank territory. These polices have affected all aspects of Palestinians' lives in the West Bank, reducing their freedoms and increasing the difficulty in accessing medical and educational services (Qato, Doocy, Tsuchida, Greenough and Burnham, 2007).

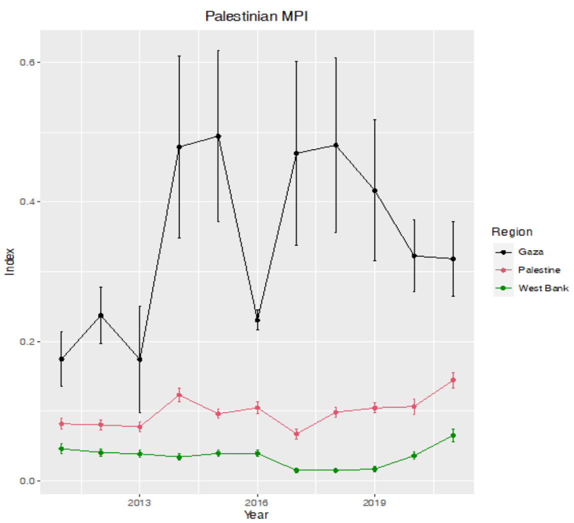
Figures 5 and 6 respectively present the state-wide model dynamics for the multidimensional poverty headcount and the Palestinian multidimensional poverty index compared with the dynamics of two separated regional models for Gaza and the West Bank. If one looks at the average simulated values, they seem to move in opposite directions in these two regions during the period covered by these simulations. This observation would constitute a strong argument for separate models in an ideal setting. However, Gaza's number of observations is too small to produce any significant results from the simulations. The 95 per cent confidence bars are very wide, making it impossible to distinguish the simulated values for any two years from one another. Two factors can explain these large confidence intervals. First, the number of observations being small in Gaza, the variability of results due to resampling in the bootstrap will be more considerable. This first channel is the only one impacting the 2016 variability. This explains the smaller size of the 2016 confidence interval. In addition to this uncertainty, there is also uncertainty around the copula's fit for other years. The checkerboard copula that we use has the advantage of being computationally relatively simple compared to other solutions when facing discrete outcomes. This analytical choice reduces the computing time of simulations substantially. However, when we move to a combination of relative positions in each indicator's marginal distributions that is not in the dataset, the copula's value for these combinations is obtained by a hyperplane interpolation, which is the equivalent of linear interpolation in a two dimensions framework. These hyperplane interpolations are more sensitive to a change of the anchor point at each iteration of the bootstrap than a smoother parametric functional form. Since we have many binary indicators for which actual observations are clustered on two relative positions in 2016, this compounds with the small sample size of Gaza and produces this large uncertainty. For this reason, we will focus on the state-wide model for the rest of the present section, keeping in mind that we face two regions that have very different dynamics.

Figure 5. Multidimensional poverty headcount trends



Sources: ESCWA calculations based on PCBS and OCHA oPt data.

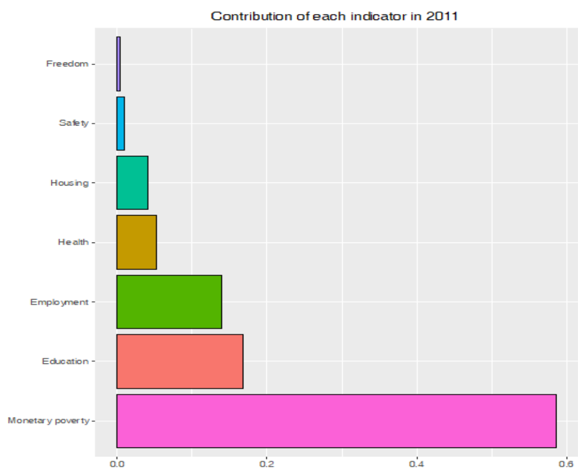
Figure 6. Palestinian multidimensional poverty index trends



Sources: ESCWA calculations based on PCBS and OCHA oPt data.

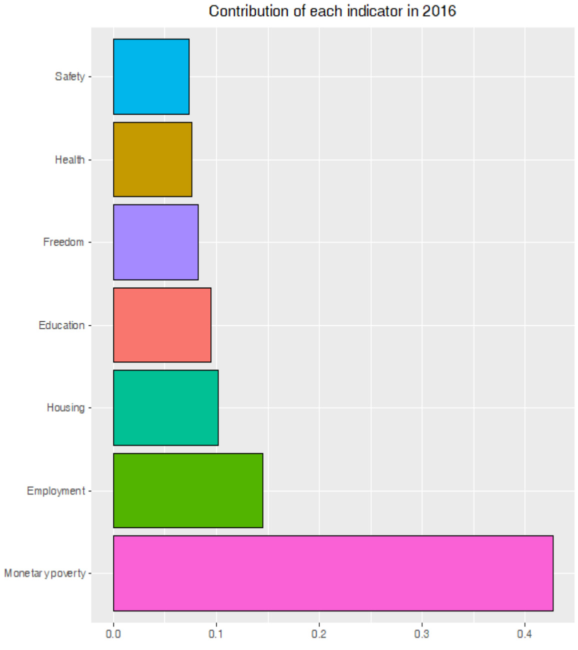
For policy and planning purposes, it is essential to analyse the dynamics of each dimension of multidimensional poverty's contribution to the total Palestinian multidimensional poverty index. Figure 7 presents this decomposition for 2011. For this year, almost 60 per cent of the simulated Palestinian multidimensional poverty index's value comes from monetary poverty. This proportion is an essential difference with the decomposition results for 2016 depicted in figure 8. In 2016, monetary poverty represented less than 45 per cent of the total contribution to the Palestinian multidimensional poverty index. However, if we look at the incidence of monetary poverty in both years, the change is not as substantial, moving from 24.8 per cent in 2011 to 23.4 per cent in 2016. Figures 2 and 3 indicate that multidimensional poverty has increased significantly between these two years. This change comes from other dimensions. A significant difference between 2016 and 2011 is that the freedom and safety dimensions that were almost not contributing to multidimensional poverty in 2011 now have more significant contributions in 2016. The contributions of employment indicators also increased substantially during this period.

Figure 7. Contributions of the different dimensions to the Palestinian multidimensional poverty index in 2011



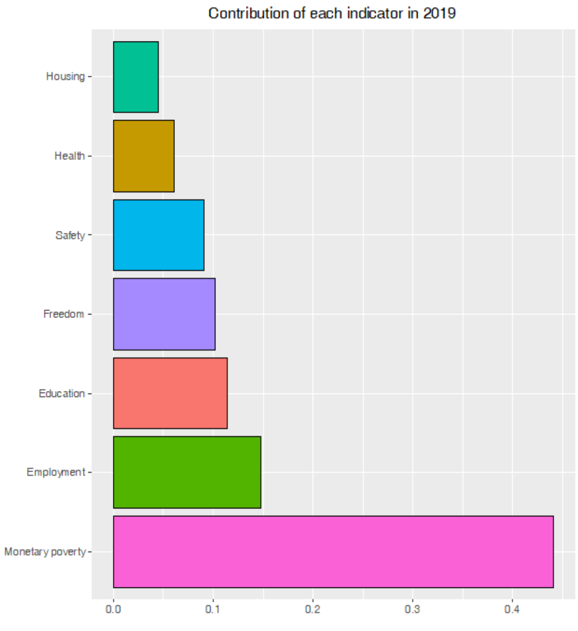
Sources: ESCWA calculations based on PCBS and OCHA oPt data.

Figure 8. Contributions of the different dimensions to the Palestinian multidimensional poverty index in 2016



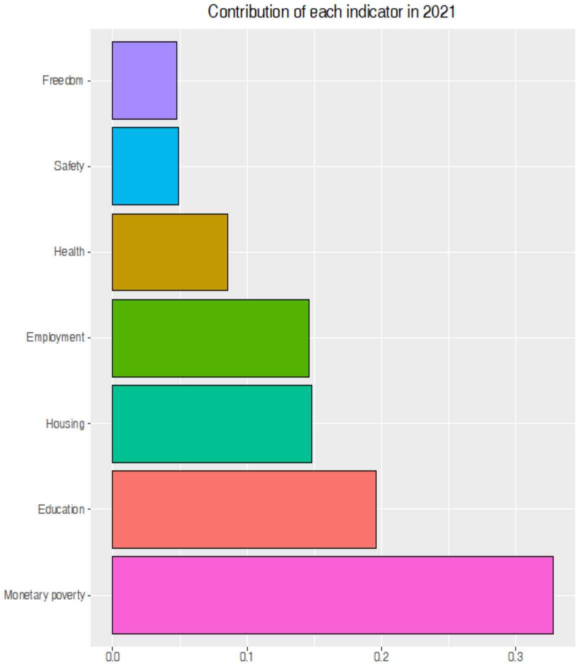
Sources: ESCWA calculations based on PCBS and OCHA oPt data.

Figure 9. Contributions of the different dimensions to the Palestinian multidimensional poverty index in 2019



Sources: ESCWA calculations based on PCBS and OCHA oPt data.

Figure 10. Contributions of the different dimensions to the Palestinian multidimensional poverty index in 2021

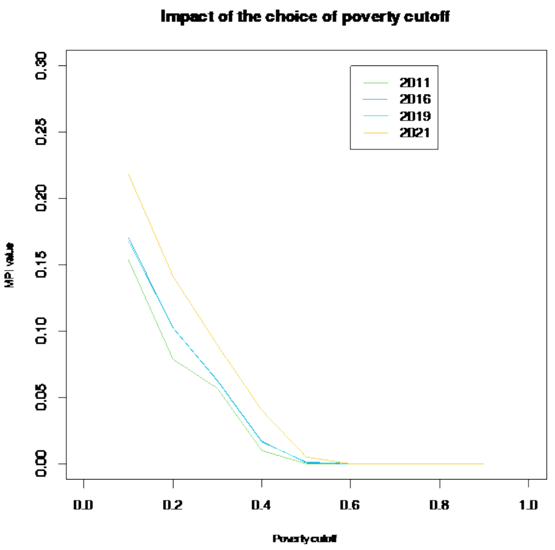


Sources: ESCWA calculations based on PCBS and OCHA oPt data.

Figures 9 and 10 present the decomposition for 2019 and 2021. Although the values of the Palestinian multidimensional poverty index are similar in 2016 and 2019, the composition of the index changes between the two years. The main change comes from a sharp decrease in housing indicators' contribution. However, this is totally reversed in the 2021 simulation. This reversal is driven in the model by the significant increase of demolition activities in the West Bank. The other critical simulated facts in 2021 that are worth considering the increase of the contribution of health, employment, and most importantly, education.

Finally, it is important to assess the simulated results' sensitivity to the choice of the poverty cutoff at 0.20. Figure 11 presents the plot of the Palestinian multidimensional poverty index values for 2011, 2016, 2019, and 2021 for all poverty cutoffs between 0.1 and 0.9. It is not surprising that the values are decreasing with the increase of the cutoffs. However, a favourable result is that the ranking of the dynamics between these years seems robust to a change of this cutoff. If one refers to the simulated values in figure 3, there was more multidimensional poverty in 2016 than in 2011, 2019 was indistinguishable from 2016, and multidimensional poverty was higher in 2021 compared to 2019 and 2016. Figure 11 indicates that this ranking remains the same for all potential poverty cutoffs.

Figure 11. Impact of the choice of the poverty cutoff on the Palestinian multidimensional poverty index



Sources: ESCWA calculations based on PCBS and OCHA oPt data.

4. Conclusion

The present report adapts the modelling approach proposed in Makdissi (2020) to the context of the Palestinian multidimensional poverty index. This modelling approach models the dynamics of the different indicators separately. This allows the model to account for the impact of changes in per capita production and political factors in addition to chronology. In addition, it proposes a method to deal with indicators that are missing in one survey year on which the model is calibrated. One main difference with Makdissi (2020) is the incorporation of political factors such as the intensity of demolition or the overall intensity of occupation in modelling the dynamics of multidimensional poverty in the State of Palestine.

The simulation results show a significant increase in deprivation of dimensions such as freedom, safety, and quality of employment in the State of Palestine from 2011 to 2016. Also, the COVID-19 pandemic simulation suggests that deprivation in education may be an important contributor to multidimensional poverty in the future.

One major drawback of the proposed model is that it cannot appropriately capture the difference in Gaza's dynamics and the West Bank separately. This disappointing result is mainly due to the small number of observations for Gaza in the survey. The modelling approach could substantially be improved in the future if the sampling design includes more observations for Gaza.

Annex 1. Estimation of the copulas

We use a Hájek estimator version of the checkerboard copula from Genest, Nešlehová, and Rémillard (2017) that accounts for the presence of survey weights. In order (Tillé, 2020) to present this estimator, we need to introduce a few concepts. Let ω_i represents the survey weight of individual i. A rank $\hat{u}(x_k)$ associated to a value x_k in indicator k is given by the Hájek estimator of the cumulative distribution:

(12) $$\hat{u}(x_k) = \hat{F}_{X_k}(x_k) = \frac{1}{\sum_{i=1}^{n} \omega_i} \sum_{i=1}^{n} \omega_i \, \mathbf{1}(x_{ik} \leq x_k).$$

Two concepts associated with the above estimator are useful in the estimation of the copula. First, the estimator of inverse of the CDF is:

(13) $$\hat{F}_{X_k}^{-1}(u_k) = inf\{u_k : \hat{F}_{X_k(x_k)} \geq u_k\}.$$

The second concept is the left limit of the CDF which is not equal to the CDF for discrete values. It is estimated by:

(14) $$\hat{F}_{X_k}(x_k -) = \frac{1}{\sum_{i=1}^{n} \omega_i} \sum_{i=1}^{n} \omega_i \, \mathbf{1}(x_{ik} < x_k).$$

the estimator is given by:

(15) $$\hat{C}(\mathbf{u}) = \frac{1}{\sum_{i=1}^{n} \omega_i} \sum_{i=1}^{n} \omega_i \prod_{k=1}^{22} \{\lambda_{\hat{F}_k}(u_k) \mathbf{1}(u_{ik} \leq u_k) + [1 - \lambda_{\hat{F}_k}(u_k)] \mathbf{1}(u_{ik} < u_k)\}.$$

Where

(16) $$\lambda_{\hat{F}_k}(u_k) = \begin{cases} \frac{u_k - \hat{F}(\hat{F}^{-1}(u_k)-)}{\hat{F}(\hat{F}^{-1}(u_k)) - \hat{F}(\hat{F}^{-1}(u_k)-)} \\ 1 \end{cases}$$

if $\hat{F}\left(\hat{F}^{-1}(u_k)\right) - \hat{F}\left(\hat{F}^{-1}(u_k) -\right) > 0$, otherwise.

In the next section of the annex, we also refer to the multidimensional survival function, $\overline{H}(\mathbf{x})$. The copula of this multidimensional survival function, $\overline{C}(\mathbf{u})$, can be estimated using equation (15) but by replacing equations (12), (13), and (14) by their survival counterpart, where the survival is $S_{X_k}(x_k) = 1 - F_{X_k}(x_k)$ for the univariate case (this is generally not true for the multidimensional case, this is why the copula of the survival should be estimated).

Annex 2. Numerical integration of the indices

To numerically compute the indices from the counterfactual distributions we simulate 10,000 22-dimensional vectors, $\mathbf{u_i}$ ($i \in \{1,2,\ldots,10{,}000\}$), for each household type. To each one of these vectors, we associate $\hat{\psi}(\mathbf{u_i}) = \widehat{\Pr}[u \in \mathcal{B}^{22}(\hat{\mathbf{u}}_\mathbf{i}^{-}, \hat{\mathbf{u}}_i)]$, where $\mathcal{B}^{22}(\hat{\mathbf{u}}_\mathbf{i}^{-}, \hat{\mathbf{u}}_i) = \prod_{k=1}^{22}[\hat{\mathbf{u}}_\mathbf{i}^{-}, \hat{\mathbf{u}}_i]$, is the 22-dimensional hyperbox defined between $\hat{\mathbf{u}}_\mathbf{i}^{-}$ and $\hat{\mathbf{u}}_i$, and $\hat{\mathbf{u}}_\mathbf{i}^{-} = \hat{\mathbf{u}}_i - (\varepsilon, \ldots, \varepsilon)$. $\varepsilon > 0$ should be chosen small enough. We use $\varepsilon = 0.0001$ in our numerical application. This probability of having an individual in the hyperbox can be expressed as $\hat{\psi}(\hat{\mathbf{u}}_i) = \Pr[\hat{\mathbf{u}}_\mathbf{i}^{-} <_K u \leq_K \hat{\mathbf{u}}_i]$, where $<_K$ and $\leq_K$ are the vectors element-wise operators. From there, it is straightforward that this expression is equivalent to:

(17) $$\hat{\psi}(\hat{\mathbf{u}}_i) = \hat{C}(\hat{\mathbf{u}}_i) \times \hat{\hat{\bar{C}}}(\hat{\mathbf{u}}_\mathbf{i}^{-}).$$

The two terms on the right-hand side of this equation can be estimated using the copula estimation described in the previous section of the annex.

The value of the indices are given by:

(18) $$\widehat{MPH}\left(H_{t:2016}^{G}(\mathbf{x})\right) = \frac{1}{\hat{\Psi}} \sum_{i=1}^{10,000} \hat{\psi}\,(\mathbf{u_i}) \mathbf{1} \left(\sum_{k=1}^{22} d_k\, \mathbf{1}\left(u_{ik} \leq \hat{F}_{X_k t}^{G}(z_k)\right) \geq c\right).$$

and,

(19) $$\widehat{MPI}\left(H_{t:2016}^{G}(\mathbf{x})\right) = \frac{1}{\hat{\Psi}} \sum_{i=1}^{10,000} \hat{\psi}\,(\mathbf{u_i}) \left[\mathbf{1}\left(\sum_{k=1}^{22} d_k\, \mathbf{1}\left(u_{ik} \leq \hat{F}_{X_k t}^{G}(z_k)\right) \geq 0.20\right) \times \sum_{k=1}^{22} d_k\, \mathbf{1}\left(u_{ik} \leq \hat{F}_{X_k t}^{G}(z_k)\right)\right].$$

where $\hat{\Psi} = \sum_{i=1}^{10,000} \hat{\psi}\,(\mathbf{u_i})$.

References

Abdelkhalek, T. and J.-M. Dufour (1998), Statistical inference for computable general equilibrium models, with application to a model of the Moroccan economy, *Review of Economic and Statistics*, 80, 520-534.

Abdelkhalek, T. and J.-M. Dufour (2006), Confidence regions for calibrated parameters in computable general equilibrium models, *Annales d'économie et de statistique*, 81, 1-31.

Alkire, S. and J. Foster (2011), Counting and multidimensional poverty measurement, *Journal of Public Economics*, 95, 476-487.

Alkire, S., R. Nogales, N.N. Quinn, and N. Suppa (2020), On Track or Not? Projecting the Global Multidimensional Poverty Index, Oxford Poverty & Human Development Initiative (OPHI), Research in Progress Series 58a.

Alkire, S., and M.E. Santos (2014), Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index, *World Development*, 59, 251-274.

Atamanov, A., S. A. Tandon, G. Lopez-Acevedo, and M. A. Vergara Bahena (2020), Measuring Monetary Poverty in the Middle East and North Africa (MENA) Region: Data Gaps and Different Options to Address Them, Policy Research working paper no. WPS 9259, World Bank Group.

Dufour, J.-M., L. Khalaf, and M. Kichian (2013), Identification-robust analysis of DSGE and structural macroeconomic models, *Journal of Monetary Economics*, 60, 340-350.

Economic and Social Commission for Western Asia, Oxford Poverty and Human Development Initiative, and League of Arab States (2020), *Proposal for a Revised Multidimensional Poverty Index for the Arab Countries*, E/ESCWA/CL2.GPID/2020/TP.11

Genest, C., J.G. Nešlehová, and B. Rémillard (2017), Asymptotic behavior of the empirical multilinear copula process under broad conditions, *Journal of Multivariate Analysis*, 159, 82-110.

Hofert, M., I. Kojadinovic, M. Mächler, and J. Yan (2018), *Elements of Copula Modeling with R*, Springer.

Khaled,M., P. Makdissi., P. Rao, and M. Yazbeck (2020), A simple unidimensional representation of multidimensional inequality, with an application to the Arab region, mimeo (available from the authors).

Khawaja, M., J. Al-Saleh, N. Reece and A. Conconi (2020), Measuring multidimensional poverty in Palestine, paper presented at the 26th Annual Conference of the Economic Research Forum for the Arab Countries, Iran and Turkey.

Klasen, S. and S. Lange (2012), Getting progress right: Measuring progress towards the mdgs against historical trends, Tech. Rep. 87, Courant Research Centre: Poverty, Equity and Growth-Discussion Papers.

Makdissi, P. (2020), A flexible approach to nowcasting and forecasting Arab multidimensional poverty, mimeo.

Qato, D., S. Doocy, D. Tsuchida, P.G. Greenough, and G. Burnham (2007), West Bank barrier decreases access to schools and health services, *Prehospital and Disaster Medicine*, 22, 263-266.

Ram, R. (2020) Attainment of multidimensional poverty target of sustainable development goals: a preliminary study, forthcoming in *Applied Economics Letters*, https://doi.org/10.1080/13504851.2020.1771265.

Smith, M. S. and M. A. Khaled (2012), Estimation of copula models with discrete margins via Bayesian data augmentation, *Journal of the American Statistical Association*, 107, 290-303.

Tillé, Y. (2020), *Sampling and Estimation from Finite Populations*, Wiley Series in Probability and Statistics.

21-00388