Impact of social protection programs on multidimensional poverty: new targeting approaches and application to Morocco

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December 22, 2021

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The original idea for this article came from work done by the authors as part of Economic and Social Commission for Western Asia (ESCWA) funded project. The authors would like to thank Mr. Khalid Abu Ismail, Senior Economist on Poverty and Human Development at the Gender Justice, Population and Inclusive Development Cluster, Mr. Vladimir Hlasny and Mrs Sama El-Haj Sleiman, for their comments. The authors would also like to thank UNICEF for providing access to the Moroccan database. The opinions expressed are those of the authors and do not necessarily reflect the views of ESCWA.

Abstract

Two new methodologies are developed to approach the impact of the reform of the social protection system in Morocco on multidimensional poverty as measured by the MPI introduced by OPHI, and its components. These approaches are distinguished by their mechanism for targeting beneficiaries. The first approach bases the identification of beneficiaries on random selection. The second approach is *a priori* more objective and based on a probabilistic model (probit). As an illustration, we use data from Morocco's 2018 *Enquête Nationale sur la Population et la Santé Familiale* (ENPSF). We consider three reform scenarios targeting health and education indicators. We present the results in ponctual form and by confidence intervals constructed using both Monte Carlo and bootstrap approaches. Finally, we perform a distributional analysis to overcome the arbitrariness of setting the poverty line associated with the measures and make robust comparisons. Our results show that the three simulated reforms have a positive effect on the multidimensional poverty measures, regardless of the approach used. At the methodological level, targeting by objective identification does not necessarily dominate random targeting for the simulations we conducted, possibly because of the highly unbalanced sample.

Key words: Social protection; Targeting; Multidimensional poverty measure; MPI; Morocco

JEL Codes: C15 ; H55 ; I 32 ; N37

1 Introduction

Since the adoption of the Sustainable Development Goals (SDGs), many countries, particularly developing ones, have been forced to review their social protection systems. These systems make it possible to fight poverty in its various aspects. To analyze the impact of these reforms on poverty, several approaches can be proposed. Concerning the impact on monetary poverty, the tools used are rather classic and capture the effect through variations in household income and expenditure. The measures of poverty used are mainly those of the Foster Greer and Thorbecke type developed in Foster et al. (1984).[1]

However, by definition, social protection programs target mainly non-monetary dimensions of the population's well-being, notably by providing access to basic services such as health and education, which can have short- and long- term effects. As a result, the poverty measures to be considered in order to approach the impact of reforms on other dimensions of poverty should also be non-monetary. In terms of measurement, these different dimensions are taken into account in the Multidimensional Poverty Index (MPI) and its components initially developed by the Oxford Poverty and Human Development Initiative (OPHI). However, the link between social protection reforms and the more complex multidimensional poverty measures has not been addressed in the literature. Indeed, despite the great interest of policymakers, donors, and researchers, there is little evidence on the impact of these programs, and very little on their effects on multidimensional poverty.

In this methodological article, we develop two original approaches *ex ante* and microsimulated that can complement each other to measure such impact. We specify both the theoretical foundations (statistical and econometric) of each of these two approaches and their practical numerical implementation.

In Section 2, we begin by presenting the dimensions and indicators used for the OPHI global MPI, as well as its revised version, developed by the United Nations Economic and Social Commission for Western Asia (ESCWA), the Oxford Poverty and Human Development Initiative (OPHI) in collaboration with the League of Arab States (LAS). We then discuss the theoretical foundations of the MPI and its two components as proposed by Alkire and Foster (2007) .

Before introducing the two approaches developed in this article that link this measure of multidimensional poverty to social protection systems, we review the definitions and the components of social protection systems (Section 3). In this same section, we identify the main connections between social protection and multidimensional poverty. Since our application focuses on Morocco, we present the main axes of the new social protection reform, initiated in 2018 (Section 3.3).

In order to approach changes in multidimensional poverty measures following the im-

[1] See for example Fiszbein et al. (2014), Satumba et al. (2017) and Bakhshinyan et al. (2019).

plementation of social protection programs, we develop in Section 4, two methods that are distinguished by their principle of targeting beneficiaries of the programs. The first method consists in selecting the beneficaries randomly from among those initially deprived according to one or more indicators of interest (Section 4.2). The second method proposed is more objective since more robust on theoretical basis. In this approach, the identification of individuals who change status (from deprivate to non-deprivate) as a result of a social protection measure are those with the highest probability of benefiting from it (or the lowest probability of being deprivate). This approach is rarely used and, to our knowledge, never in the context of measuring the impact of social protection programs on multidimensional poverty (Section 4.3).

To illustrate the approaches we develop, we calculate in Section 5, the MPI for Morocco using the *Enquête Nationale sur la Population et la Santé Familiale* (ENPSF) of 2018. We then propose three reform scenarios as extension and generalization of social protection in Morocco. The simulations target two health indicators and one education indicator considered in the MPI.

In Section **??**, we present our results in two ways. First, we examine the results on a ponctual and interval level using both Monte Carlo and bootstrap approaches. This allows us to compare the results obtained from the two approaches developed. Second, a distributional analysis is conducted using three statistical concepts, density functions, stochastic dominance and incidence curves, to compare the distributions of individual deprivation measures at the MPI level between the baseline and each scenario. The final section concludes and points some extensions (Section 6).

Our results show that as expected, all simulated reforms have a positive effect on multidimensional poverty measures, no matter which approach is chosen. While we would anticipated a social protection policy to be much more effective when it objectively targets the beneficiaries of the reform, we find that the relative changes are almost always larger in absolute values under random targeting than under objective identification. This result can be explained by the fact that the probit models estimated were done with an unbalanced sample in addition to the fact that households and deprivate individuals could be homogeneous.

The methods developed are very relevant for explicitly identifying and assessing the link between social protection programs and multidimensional poverty and can be used for any number of indicators and in any country.

2 Multidimensional Poverty Measure - MPI

In order to approach and measure poverty on non-monetary basis, a multidimensional method was proposed by Alkire and Foster (2007) (AF).[2] On this base and in the frame-

[2]This article was published a few years later in the *Journal of public economics*. See Alkire and Foster (2011).

work of the Oxford Poverty and Human Development Initiative (OPHI), a Multidimensional Poverty Index (MPI) has been developed. It was adopted by the United Nations Development Program (UNDP) from 2010 in order to monitor and translate annually the deprivations of households in more than 100 developing countries. It is regularly published in the UNDP's Human Development Report.[3]

2.1 Dimensions and indicators

The *Global MPI* is based on non-monetary deprivation and has three dimensions: health, education and standard of living. These three dimensions are declined into ten indicators that are supposed to better describe the situation of poor households and individuals. The *Global MPI* characterizes deprivation and poverty at the individual and/or household level. In this approach, when necessary, characteristics observed at the household level are considered to be valid for all members of that household.

Furthermore, to develop the Arab World Poverty Report, ESCWA (2017) adopted a revised multidimensional poverty index (MPI) to calculate and decompose it for several Arab countries. The MPI of ESCWA is composed of the three dimensions of the *Global MPI*. It does, however, include fourteen indicators. The education dimension consists of three indicators: school attendance, years of schooling, and delayed schooling.[4] The health dimension includes three indicators: nutrition, child mortality, and early pregnancy. The standard of living indicators selected are: access to electricity, adequate sanitation, safe drinking water, clean cooking fuel, adequate floor and roof space, absence of overcrowding or overcrowding in the household dwelling, and access to a minimum of information, mobility, and amenities in the dwelling.[5]

In this approach, to classify a household as deprived or not on a specific indicator, its value or level of achievement on that indicator is compared with a pre-established deprivation threshold. These thresholds used generally correspond to widely accepted standards, such as the United Nations Educational, Scientific and Cultural Organization (UNESCO) compulsory years of schooling, the World Health Organization (WHO) standards for malnutrition and anthropometric measures for ages of individuals, the United Nations Human Settlements Programme (UN-Habitat) persons per room, etc.

The annexed Table 4 reports the indicators used in the ESCWA MPI calculation, specifying the different definitions and thresholds used for acute poverty and poverty and the weights associated with these indicators. In particular, it shows that the definitions

[3] Alkire and Santos (2014) provide the theoretical and practical details of how this index is calculated.

[4] In the case of Morocco, this indicator is not included, which reduces the number of indicators to 13.

[5] The selection of the dimensions and indicators for the MPI of ESCWA is based on two main sources. The first is the dimensions and indicators selected from OPHI's *Global MPI*. The second was a participatory process consisting of conferences organized by ESCWA with partners from the League of Arab States and Ministries of Social Affairs from across the region. The objective was to address regional priorities in the Arab region. The MPI of ESCWA technical team of course took into consideration the data available in the surveys accessible in the different countries.

of deprivation on several indicators are more restrictive than those used by OPHI in its measure of the *Global MPI*. This generally leads to higher deprivation rates per indicator under the ESCWA definitions resulting in a higher MPI value. We also present the adjustments made in the case of Morocco for the indicators, weights and deprivation thresholds. Indeed, for this country, only 13 indicators are used, which implies adjustments to the weights.

When proposing its version of the MPI, the ESCWA had several objectives. First, it aimed to ensure that the measure remains a useful tool for making regional comparisons across countries and also sub-national comparisons. In this sense, the ESCWA MPI should help the geographic targeting of poverty reduction in all its dimensions within and across Arab countries in particular. It could also guide public policies in prioritizing actions to be taken and in allocating scarce resources. The ESCWA MPI assessment should also help countries and international donor agencies to make informed decisions about targeting beneficiary areas and countries to reduce multidimensional poverty in the subregion. More generally, the ESCWA wanted the MPI to be a reference and benchmark for better assessing progress in development and social protection in the countries of the subregion.

2.2 Theoretical foundation of MPI

As explained in the previous section, in order to assess the measurement of multidimensional poverty, one must first identify the dimensions to be covered and the associated indicators. These are then compared to deprivation thresholds. These indicators are then aggregated into a synthetic measure that is compared to a pre-established threshold. In this way, it is possible to identify individuals who are deprived according to each indicator and the poor in a multidimensional way. In this section, building on Borga et al. (2020), we present the approach developed by Alkire and Foster (2007) and Alkire and Foster (2011) to measure multidimensional poverty. As in Foster et al. (1984), the MPI is obtained by computing and weighting the deprivations suffered by individuals on the basis of the indicators mentioned above. Formally, let us suppose that we have a population with n individuals and let $d \geq 2$ be the number of indicators considered. Let $y = [y_{ij}]$, the matrix $(n \times d)$ of basic data such that $y_{ij} \geq 0$ is the observation of individual i $(i = 1, 2, ..., n)$ for indicator j $(j = 1, 2, ..., d)$. Let z_j be the threshold below which an individual will be considered deprivate according to indicator j. On the basis of these d thresholds, we can construct the deprivation matrix g^0 such that $g^0 = [g^0_{ij}]$ of dimension $(n \times d)$. Thus, we will have $g^0_{ij} = 1$ when $y_{ij} < z_j$ which means that individual i is deprived according to indicator j and $g^0_{ij} = 0$ when $y_{ij} \geq z_j$.

Furthermore, let w_j be the weight associated with indicator j such that $0 \leq w_j \leq 1$ and $\sum_{j=1}^{d} w_j = 1$ (Alkire and Foster, 2011). It is then possible to construct a vector of deprivation scores c of dimension $(n \times 1)$ from the matrix g^0 and the weights w_j such that

$$c_i = \sum_{j=1}^{d} w_j g_{ij}^0 \quad \forall i = 1, 2, ..., n. \tag{1}$$

the i^{th} component of this vector represents the sum of the weights of the indicators for which the individual i is deprived.

Furthermore, in order to identify multidimensionally poor individuals, Alkire and Foster (2011) propose an identification method according to which individual i is multidimensionally poor when the sum of the weights of the indicators in which he is deprived is greater than or equal to k, where k is a threshold chosen by the researcher or the decision maker. In other words, this threshold k is applied to the vector c such that the individual i will be multidimensionally poor if $c_i \geq k$ and not poor when $c_i < k$.

Finally, different indices are calculated in the last step to measure poverty: 1- the incidence of multidimensional poverty, H; 2- the average poverty gap or poverty intensity, A; and 3- the adjusted incidence, which is the MPI and which we will note M.

The incidence of poverty measures the proportion of individuals in multidimensional poverty equal to $H = \frac{q}{n} = \frac{1}{n}\sum_{i=1}^{n} q_i$ with q_i an indicator variable when individual i is poor and q the number of multidimensionally poor individuals. The intensity of poverty is the average of the weighted deprivations of multidimensionally poor individuals such that $A = sum_{i=1}^{q}\frac{c_i}{q}$. Finally, the adjusted incidence, M, is a combination of the incidence and intensity of multidimensional poverty such that $M = H \times A$. It represents the share of the population that is multidimensionally poor, adjusted by the intensity of deprivation that this population experiences. M thus summarizes the incidence and intensity of multidimensional poverty. In this paper, we will therefore assess the changes observed in H, A and M following the implementation of a reform of the social protection system in Morocco.

3 Social protection and multidimensional poverty

In order to cross-reference the dimensions of the MPI with social protection programs, we briefly review the concept of social protection and its components. The objective is to identify the indicators covered by the MPI that are likely to be impacted by the reform of the social protection system in Morocco.

3.1 Definition and content of social protection

Social protection is intrinsically linked to the Sustainable Development Goals (SDGs), particularly in the implementation of measures to ensure adequate coverage of the poor and vulnerable by 2030. This is especially true in the context of achieving Goal 1: *eradicate poverty in all its forms worldwide.* But what do we mean by social protection?

There seems to be no consensus definition of what social protection is. However, most of the definitions we find in the literature emphasize the implementation of measures aimed at fighting poverty and vulnerability, notably by preventing the risks that these individuals face throughout their lives.
Boccanfuso et al. (2018) define social protection as a broad concept, including all government interventions providing support or services to individuals. This support can then follow two logics, either assistance or insurance. Indeed, social protection systems affect a multitude of policy areas (children, households, maternity, unemployment, sickness, old age, disability, ...) either through contributory schemes (social insurance) or through non-contributory and tax-financed benefits (social assistance) (OIT, 2017). Holzmann and Jørgensen (2001) place social protection in a context of social policy and risk management. They define it as government interventions to help individuals, their households, and communities better manage risk and support the poor. Interventions should help prevent, mitigate, and enable beneficiaries to adapt to situations that could push them into poverty, such as the loss of a job. Zhang et al. (2010) also see social protection as a means of combating both chronic and transitory poverty and vulnerability. For these authors, it is about policy interventions aimed at improving the well-being of all but more particularly, youth, unemployed, working poor, or vulnerable groups in the population such as disabled or elderly.
The World Bank, UNICEF, and many other international agencies view social protection as a set of policies and programs that aim to prevent and protect individuals from shocks that may occur throughout their lives and that improve resilience, equity, and opportunity. The difference in the definitions proposed by these organizations lies in the target population (children, women, elderly, people with disabilities, migrants, etc.) and the way in which these supports are proposed and implemented.
Most countries have insurance-type measures, especially for unemployment or retirement. Contributions are deducted from workers and in the event of a crisis or recession, these can be reduced and compensated by public funds. The vast majority of Middle East and North Africa (MENA) countries have a pay-as-you-go pension system set up after independence. However, most of these countries target the deprivate sector and civil servants, and these systems are in part supported by governments. It appears that the effects of these measures on poverty are often weak or non-existent and that they have increased inequality, given the nature of the targeting.
In terms of assistance-type social protection, the measures observed are designed to reduce the vulnerability of low-income households so as to supplement or compensate for their consumption needs, but also by extending its coverage, particularly by providing access to basic services such as health and education. Thus, social protection must ensure a better smoothing of consumption over the whole life cycle of households and individuals and thus fight against poverty and vulnerability, both monetary and non-monetary. These measures must also ensure that an acceptable standard of living is maintained in

the event of a shock to households. These interventions aim to promote social inclusion and equity and also ensure the political and social stability of the countries.

Social protection relies on a diverse range of measures. Among these, non-conditional cash transfers, whether universal or not, aim to guarantee access to essential services to the population (family allowances for children) or groups targeted as poor or vulnerable. Conditional cash transfers target poor households who are required to perform specific actions, such as performing community service, in return for which they receive cash grants. These transfers can also be income conditioned. In some cases, conditionalities could be linked to enrolling and keeping children in school or to medical monitoring imposed on children or pregnant women. In-kind transfers are an essential pillar of social protection, particularly in developing countries. We find, for example, the allocation of food and supplements, school feeding or the distribution of food in emergency situations. This kind of measure has multiple benefits as it directly addresses food security and related nutritional aspects and will have a positive impact on the retention and success of children in school. These measures can be conditional (being effectively enrolled and present at school) and could also be adapted to specific situations (market days or harvest periods). Other social protection measures include market interventions such as price controls and subsidies for certain commodities (food price supports, subsidies for energy goods (fuel, electricity, etc.)). Still others are attributable to fee waivers including full or partial coverage of health or education costs.

Given the budgets associated with the social protection measures deployed by governments, current orientations seem to favor better targeting of poor and vulnerable populations by considering not only the direct effects of these measures but also the induced effects, including in the medium and long terms.

3.2 Crossing dimensions of multidimensional poverty and social protection

No matter what form they take, social protection measures are intended to have an impact on poor and vulnerable populations. These impacts can be monetary through a direct increase of income or expenditure and thus have an effect on monetary poverty. They can also reduce poverty in a multidimensional framework by providing access to education or health, for example. By crossing these social protection measures with the dimensions and indicators that compose the MPI, it is possible to see how, depending on the objectives in terms of the fight against multidimensional poverty, the measures could be designed. The first two dimensions (health - nutrition and education) can be achieved by all forms of social protection, whether monetary or in kind. On the other hand, access to services will be promoted by non-monetary measures. This intersection is all the more important as it is now recognized that poverty and vulnerability can differ from one country to another or even from one environment to another. These social protection measures must therefore take into account these socioeconomic differences so that impacts based on the resilience of these people incorporate these dimensions. For example, in many countries, school feeding programs have been implemented. Their impacts are both nutritional and educational, as better-fed children will do better in school. In addition to these dimensions, the incentive to send children to school becomes more important for parents since the school takes over part of the household food expenses. These school canteens also reduce gender inequalities in access by encouraging parents to send girls to school. This measure could also help reduce child labor. These social protection programs have direct effects and these will be felt throughout the life cycle of children, possibly affecting social mobility.

Another important aspect in the intersection of social protection measures and their impacts on multidimensional poverty is to link them to the Sustainable Development Goals (SDGs), particularly in order to monitor countries' progress. It should be recalled that target 1.3 of the SDGs aims to "*Establish social protection systems and measures for all, appropriate to the national context, including social protection floors, and ensure that by 2030 a significant proportion of the poor and vulnerable benefit from them*". A second Goal is also directly related to a social protection system, namely target 3.8: "*Ensure that everyone has access to universal health coverage, including financial risk protection and access to quality essential health services and to safe, effective, affordable and essential medicines and vaccines*". (OIT, 2017).

ESCWA2017 cross-references its proposed MPI indicators with those of the SDGs. According to the Organization, 8 of the 17 MDGs overlap with the indicators of the MPI, namely those related to nutrition, health, education, gender equality and empowerment, water and sanitation, clean energy and housing. In addition, there is Goal 13 to fight climate change. Indeed, in recent years, the effects of climate change have been taken into consideration in the development of social protection measures. These adaptive social protection measures to mitigate the effects of climate change aim in particular to fight against poverty and vulnerability (resilience of agricultural households) but also to fight against malnutrition. Among these measures, we find subsidies for food, water and energy services; subsidies for employment-generating programs and work programs in agriculture, ... Thus, it appears that the intersection between social protection measures and MPI indicators is obvious. In the following section, we present the main features of the social protection system in Morocco.

3.3 Social protection in Morocco

Like many countries, Morocco has a social protection system with insurance and assistance dimensions. The country's first social assistance law dates from 1942. Seventeen years later, the Social Security Act was signed. Since then, many additions have been made on a regular basis, such as the *Régime d'Assistance Médicale* (RAMED) initiated

in 2008, implemented in 2011 and generalized in 2017. These scattered measures concern old age, illness, health (especially for women/mothers and children), disability, unemployment for individuals or, at the household level, family allowances.
In 2015, the *Ministère des Affaires Générales et de la Gouvernance* in collaboration with UNICEF presented a comprehensive overview of the social protection system in Morocco during the 1^{first} *Assises nationales de la protection sociale* (MAGG, 2018). For example, through health-oriented programs such as mandatory medical insurance [6] and RAMED, the medical coverage rate has reached 61% (MAGG, 2018). The exhaustive census of measures and programs carried out by MAGG (2018) has made it possible to evaluate that social protection represents a little less than 30% of the Moroccan State budget. However, it was found that this system includes a multitude of programs with little coordination, resulting in significant overlap and leaving some groups of the population without coverage (Chemillier-Gendreau, 2018). Thus, Morocco has become aware of the need to fundamentally revise its social protection system. This realization accelerated with the advent of the COVID-19 pandemic and its consequences.
Within this context, at the highest level of the Government, the generalization of social protection has been set up as a national priority and as a structuring project. The reform proposed through several texts of law is articulated around four axes with precise deadlines: 1- The protection of the hazards of the disease through the generalization of the mandatory medical insurance (AMO) at the end of 2022; 2- The protection of the hazards relating to the childhood which should allow the households which do not have this protection to benefit from lump-sum indemnities in the form of family allocations. This program should help to fight against school dropout; 3- The protection of hazards related to old age would seek to broaden the base of members of pension systems and 4- The protection of hazards related to the loss of employment with the redesign and generalization of the compensation for loss of employment by 2025. In the spring of 2021, the King of Morocco presided over the launching ceremony of the generalization of social protection. A framework law has been prepared by the government for the implementation of the latter. This law amends a series of regulations that have been in force up to now.[7]
A parallel project initiated in 2018 has been accelerated. It consists of the adoption and implementation of a Unique Social Register (USR) which would allow a better targeting of the categories of the population eligible for aid.
All these elements testify to the importance of social protection on the Moroccan authorities' agenda. In this article, we present scenarios that simulate the impact of some of these reforms on the MPI and thus see the gains that Morocco could make in terms of multidimensional poverty reduction. In the next section, we present the methodology developed to conduct these simulations.

[6] In French, this program is called : *assurance médicale obligatoire* - AMO.
[7] For details, see `https://www.finances.gov.ma/Fr/Pages/detail-actualite.aspx?fiche=5427.`

4 Impact of Social Protection Programs on PMI: Methodology and Data

The objective of this article is to approach the variations in multidimensional poverty measures resulting from the implementation of a social protection program. The proposed approaches are microsimulated. In this section, we develop two impact analysis methods that can complement each other to measure the impact of social protection programs on the MPI.

4.1 Methodological issues

Social protection programs are intended to improve some of the indicators included in the MPI dimensions, as discussed in the section on crossovers (section 3.2). However, to have the expected effect, several difficulties exist. First, the question of targeting arises. Indeed, the first problem facing the decision-maker is to identify who should or should not benefit from the measure. Second, even when targeting is perfect for one of the MPI indicators, there is no guarantee that the MPI itself will change. This is naturally evident when one seeks to simulate the impact of social protection reforms on multidimensional poverty approached by the MPI such as those we simulate in this article.

By definition, a social protection program should change the modality of an individual i for the indicator j targeted by the program from deprivate 1 to non-deprivate 0. Formally, according to the notations introduced earlier g^0_{ij} goes from 1 to 0. The problem associated with targeting in terms of the impact on multidimensional poverty is that some individuals i deprivate according to indicator j and who benefit from the program are not necessarily multidimensionally poor. For these individuals, $c_i < k$ and therefore they are not counted in either the incidence (H) or the intensity (A) measure. Thus, the fact that these individuals benefit from the program will ultimately have no effect on the multidimensional poverty index (M).

Another possible situation is that some individuals receiving the social protection program are deprived on the j indicator and also poor in the multidimensional sense. In this case, it is possible that g^0_{ij} goes from 1 to 0 after the measure is implemented and that c_i decreases, which would reduce the intensity (A) without necessarily reducing the incidence (H). Indeed, it is possible that these individuals remain poor in the multidimensional sense, i.e. c_i, since the sum of the weights of the other deprivations remains high even after having benefited from the program that targets indicator j. In this case, the measure of multidimensional poverty M would change as a result of the change in intensity A only. Both of these situations must therefore be taken into consideration when approaching and assessing the impact of social protection programs on multidimensional poverty.

In this article, we systematically address these problems by proposing two different approaches that can also be combined. In addition to evaluating the ponctual effects of social protection programs on the magnitudes of interest captured by a simulation s and that we will note A^s, H^s and M^s, we construct confidence intervals with a level of 95% that allow us to check if the difference obtained between the initial measure and the simulated one is statistically significant. These confidence intervals also allow us to make comparisons of these measurements, in some groups of interest.

4.2 Random selection targeting

The first method consists of randomly selecting households (and therefore individuals) from among those that were initially deprived on one or more of the indicators of interest and that, because of the social protection measures, are no longer in a situation of deprivation for this or these indicators. In practice, Hoddinott (1999) shows that targeting is not a simple step to implement and that in some cases, a random intervention among deprivate households on the targeted indicator is less costly, especially administratively, and more efficient than a measure requiring complex targeting. This idea is also taken up by Coady et al. (2004), which is why we initially applied this simpler approach.
Thus, in this approach, we randomly draw a number of households (without replacement) among those being deprived for one indicator (or for several, depending on the s scenario) before the implementation of the measure (i.e. at baseline).[8]. This draw can also be done according to a pre-selected stratification by the decision-maker. For example, a social protection measure could target individuals according to their place of residence (rural, urban) or at the regional level. In our case, we draw on the proportion of households initially deprived in one or more indicators, according to their place of residence.
Once this random draw is done, we construct the new deprivation matrix $g^{0s} = [g^{0s}_{ij}]$ with the new vectors obtained from the initially deprived individuals (such that $g^{0s}_{ij} = 1$) and which through the draw of their household have become non-deprivate under the indicator j and thus $g^{0s}_{ij} = 0$. From this point, it is possible to deduce the new value of the deprivation score suffered by individual i, c^s_i from equation 1. Using the same threshold k, we can then recalculate the incidence (H^s), the intensity (A^s) and the multidimensional poverty index (M^s) from this new deprivation vector c^s.
By construction, these results provide only a punctual estimate of the three measures related to the selected random sample. To allow more robust comparisons with the baseline situation, we use Monte Carlo simulations. This technique has the great advantage of allowing (random) tests to be performed whatever the true baseline distribution of the sample (Dufour and Khalaf (2001); Efron (1981)). In practice, for each of the r replicas under the s scenario, we compute the A^s, H^s, and M^s measures, and then deduce the

[8]The random draw must be done at the household level in such a way that when a household changes its status from 1 to 0 on an j indicator, all the individuals within this household change their status. To do this, we used the Stata command *randomtag*

mean value of each of these measures which represents the point value estimate. We can then calculate the percentage changes from baseline for each of the three measures. The Monte Carlo method also allows us to construct confidence intervals for each measure and thus to evaluate the statistical significance of the observed change for A, H and M. We apply this approach in all the scenarios considered.

4.3 Objective identification targeting

We propose a second, apparently more objective method than the previous random approach, based on statistical and econometric concepts introduced by Gourieroux et al. (1987). In this approach, the identification of households that change status (from deprivate to non-deprivate) following the introduction of a social protection measure is done among those with the highest probability of benefiting from it (and therefore the lowest probability of being deprivate). The estimation of the probability at the base of the identification is done from a discrete choice model (probit in our case) taking into consideration the generalized residuals as introduced by Gourieroux et al. (1987) and taken up by several authors including, among others, Hsiao et al. (2007) and Wooldridge (2014). This approach, which seems interesting to apply, is rarely used[9] and to our knowledge, never in our context.

We consider the probability that the household i[10] be deprivate on the MPI indicator j such that $p_{ij} = P(y_{ij} = 1) = \Phi(x'_{ij}\beta_j)$ with x_{ij} a vector of K characteristics of i, β_j a vector of K parameters, and $\Phi(.)$ the distribution function of the centered reduced Normal distribution. This probit model is usually associated with a linear latent variable model, y^*_{ij}:

$$y^*_{ij} = x'_{ij}\beta_j + e_{ij} \tag{2}$$

with e_{ij} the error term which follows a centered reduced Normal distribution. After estimating the probit model, the estimated probabilities $\hat{p}_{ij} = \hat{P}(y_{ij} = 1) = \Phi(x'_{ij}\hat{\beta}_j)$ are deduced for each household i whether it is deprivate or not, according to the indicator j. The generalized residuals for this model are then deduced such that:

$$\tilde{e}_{ij}(\hat{\beta}_j) = \frac{\phi(x'_{ij}\hat{\beta}_j)}{\Phi(x'_{ij}\hat{\beta}_j)[1 - \Phi(x'_{ij}\hat{\beta}_j)]}[y_{ij} - \Phi(x'_{ij}\hat{\beta}_j)]. \tag{3}$$

where $\phi(.)$ is the density function of the centered reduced normal distribution. The adjusted probabilities that would be the basis for the household rankings are given by $\tilde{p}_{ij} = \tilde{P}(y_{ij} = 1) = \Phi(x'_{ij}\hat{\beta}_j + \tilde{e}_{ij}(\hat{\beta}_j))$. Intuitively, the residuals $\tilde{e}_{ij}$ can be interpreted as estimates of the random errors e_{ij} of the equation 2.

In practice, on the axis that represents the vector $\tilde{p}_j$ of the $\tilde{p}_{ij}$ values, we identify the

[9] See for example Robichaud et al. (2014) and Tiberti and Tiberti (2015).

[10] In this subsection, in order not to complicate the notations, we use the index i to refer to the household of individual i.

percentiles and/or the numbers determining the share of deprivate households in the baseline situation and those that remain so after the implementation of the social protection measure as defined by the policy makers.

Theoretically, this method should lead to better targeting and thus a greater reduction in multidimensional poverty measures than that obtained with a randomized approach. However, to obtain this result, it is assumed that the x_{ij} vector of K household characteristics used to predict the probability of being deprived for indicator j is relevant. In other words, this assumes that the estimated probit model has good fit and predictive power. If not, it is not clear that this method improves on the results obtained with random targeting and may even lead to less effective targeting.

Moreover, according to the MPI definition, we consider that all individuals of a household deprived on an indicator j are also deprived. On this basis, multidimensional poverty measures are computed at the individual level for both the baseline and the replications of each scenario. Then, in order to be able to construct simulated confidence intervals for the A, H and M measures, the whole proposed approach is done in bootstrap (r replicas). Each replication produces a baseline different from the baseline obtained from the survey data since the chosen sample is different. It also produces for each simulation s, a new vector of deprivations of the indicator j which replaces the baseline one to generate new measures A^s, H^s and M^s for each replica r. As in the Monte Carlo case, averages between the r replicas of the values of A^s, H^s and M^s are computed and compared with the average of the r replicas of the baseline also obtained by bootstrapping. Bootstrap confidence intervals are finally computed for the reference situation and the three simulations.

Furthermore, in order to deepen the comparison, we complete it by performing a distributional analysis based on the variables (vectors) of the post-simulation deprivation scores, c^s and the baseline c. Each of these vectors is deduced in the bootstrap by taking the means over the r replicas considered for each individual i. The distribution of the basis vector changes from one simulation to the other for individuals *multidimensionally* poor to the baseline situation. To conduct this distributional analysis, we consider an approach based on density function, distribution function (first-order stochastic dominance) and incidence curve on the four deprivation vectors. This analysis gives information on the improvement in terms of deprivation whatever the k threshold that might be retained.[11]

[11] It should be noted that these analyses are similar to those typically conducted at the monetary poverty analysis. However, in our case, by definition, the multidimensionally poor are on the right tail of the c-distribution.

5 Data, scenarios and results

5.1 Data and Moroccan MPI and measurement in 2018

In this article, we use the 2018 *Enquête Nationale sur la Population et la Santé Familiale* (ENPSF). It was conducted by the Moroccan *Ministère de la santé* with technical assistance from several partners (UNICEF; WHO; UNFPA; the Arab League and ANAM). The survey coincided with the completion of the implementation of the *Stratégie sectorielle de la santé 2012-2016* and before the advent of the global health crisis related to COVID-19. One of the objectives of this Strategy has been to assess progress in achieving the Millennium Development Goals and more recently the Sustainable Development Goals in Morocco.
Among the various questionnaires in the survey, the household one covers all household members and their characteristics (sex, age, marital status, education level, occupation, medical coverage, prevalence of chronic diseases, anthropometric measurements for children under five). It also provides information on the type of housing, access to water, electricity and sanitation, comfort elements, etc. The women's questionnaire includes questions about the birth and death history of children in the five years prior to the survey date. *De facto*, several demographic, health, and socioeconomic indicators, particularly those related to the measurement of the MPI, can be calculated from this survey.

Table 1: Multidimensional Poverty in Morocco - Situation in 2018

	Incidence of poverty (H)	**Intensity (A)**	**Multidimensional poverty index (M)**
Morocco 2018	0,1930	0,4267	0,0824

Source: Authors based on ENPSF data - 2018

The survey successfully reached 15,022 households, of which 8,788 urban and 6,234 rural. The total number of individuals surveyed was 67,795.[12] In terms of multidimensional poverty calculated with the revised ESCWA MPI presented earlier and adapted to the case of Morocco (see the table in the Appendix 4), the incidence of multidimensional poverty (H) is less than 20% (19.30%). The intensity is 42.67% . Finally, the multidimensional poverty index, M in Morocco in 2018 is equal to 8.24%. When we look at the shares of deprived individuals by dimensions (Table 2), we find that the highest deprivations are associated with the dimensions relating to the level of education of those over 18 years of age (56.02%) as well as the means of mobility (61.57%). The indicators for which deprivation is lowest in Morocco in 2018 are child pregnancy (0.97), means of communication (0.82), and child mortality (1.06).[13]

[12]The valid records in the file we used were for 67,412 individuals.

[13]As explained earlier, the deprivation thresholds used by the ESCWA are more restrictive for some indicators than those used by OPHI or the Haut-Commissariat au Plan (HCP) of Morocco to calculate

Table 2: Frequency of deprivate individuals (in percent) - 2018

Dimensions	Health and nutrition**Indicators**	**Percentage rate**
Health and nutrition	Child mortality	1.06
	Early pregnancy	0.97
	Child Nutrition	7.94
Education	School attendance	14.62
	Age schooling gap	-
	Educational attainment	56.02
Housing	Overcrowding	20.19
	Type of dwilling	18.60
Access to services	Improved drinking water	29.22
	Improved sanitation	33.91
	Electricity	2.66
Assets	Communication assets	0.82
	Mobility assets	61.57
	Livelihood assets	5.83

Source: Authors based on ENPSF data - 2018

5.2 Simulation scenarios

Given the new social protection strategy currently being implemented in Morocco and discussed in the previous section, the dimensions of the MPI that are expected to be impacted are health and education through the first two axes of the strategy. More specifically, the following three indicators are considered in our scenarios: infant mortality, malnutrition of children under 5 years of age, and school enrollment of children aged 6 to 17 years. In this article, in order to illustrate the use of the methodology developed, we simulate three scenarios.[14] At this point, it is important to specify that the proposed scenarios are assumed to be the result of different programs or actions contained in the social protection reform. It is therefore not the intention of this article to propose measures that would make it possible to achieve the simulated objectives.

In the first scenario, we assume, all other things being equal, that Morocco will achieve, through different programs, a 50% reduction in the infant mortality deprivation rate from its 2018 level (from 1.06% to 0.53%) and in the malnutrition deprivation rate from its 2018 level (from 7.94% to 3.97%).

Note that the meaning we give to the change in deprivation status on a given indicator refers to an improvement that would be observed in a future survey, not a change for the individual affected by that deprivation in 2018. For example, a change on the indicator related to infant mortality does not mean that the deprivate household no longer observes the event (loss of an infant) but rather refers to a lower rate of deprivation on this indicator that we might observe in a future survey, for other households following

the MPI. This is the case, for example, for overcrowding in housing and access to improved drinking water and sanitation.

[14] This methodology can be applied to many policies that impact different indicators covered by the MPI.

the implementation of the social protection system.
For the first indicator (child mortality indicator), given the low level of deprivation, we consider only the approach with random selection of beneficiary households, taking into account the distribution of these households according to their aera of residence (urban and rural). Indeed, modeling a discrete choice variable (in this case, being deprived) would produce unreliable results in terms of predicted probabilities when the samples are highly unbalanced.[15]. For the malnutrition indicator, we propose two approaches: 1- as for the child mortality indicator, we consider a random selection of beneficiary households; 2- we estimate the probability of being deprived for this indicator using a probit model as described in section 4.3. In the latter case, the households with the lowest probability of being deprived will be assumed to be the beneficiaries of the system reform.
In the second scenario, we assume, all other things being equal, that the deprivation rate in terms of schooling for children aged between 6 and 17 falls from its 2018 level of 14.62% to 7.31% in the future. In this scenario and for this indicator, we proceed in the same way as before by applying the two approaches, i.e. random targeting of beneficiaries among deprivated households on this indicator in 2018 and then applying targeting by objective identification on the basis of a probit model.
Finally, in the third scenario, we combine the previous two scenarios by considering the improvements in deprivation presented for the health and education indicators considered earlier. The targeting approaches are similar to those mentioned above.

5.3 Results

We begin by reporting the three measures H, A, and M and their simulated confidence intervals for the baseline and for the three scenarios. We also compare the results obtained with the randomized targeting approach and with objective targeting. As we pointed out in Section 4, in order to have a good fit of the probit model for better targeting with the objective approach, we have performed estimation with selection of the type *backward-stepwise*. The variables initially introduced in the models are the area of residence, the gender and age (and its square) of the head of household, his or her level of education and marital status, and the size of the household and its square. Finally, we consider the continuous variable relating to the household wealth score available in the database and calculated from information on household ownership of consumer durables, access to basic services, and other characteristics introduced in a factor analysis. Finally, we present the results of the distributional analysis.

[15]See for example, Maddala and Lahiri (1992), Cramer (1999), Greene (2000) et Salas-Eljatib et al. (2018).

5.3.1 Results of the punctual analysis

Under the random draw approach for all indicators considered in the scenarios and to construct confidence intervals for the different multidimensional poverty measures of interest, we adopted a Monte Carlo approach with 1,000 replicas. The first part of the table presents the results for randomized targeting for all indicators. The comparison baseline is the one obtained from the baseline survey data. The point estimate of the measures and their confidence intervals are therefore constructed using the Monte Carlo method.

The second part of the table reports the reference situation for the objective approach, which is different from that used in the randomized approach. Indeed, as explained earlier, this reference is obtained by the bootstrap method with 1,000 replicas and with a sample size fixed at 13,500 households (by imposing a random draw without replacement). The point estimate and associated confidence intervals are obtained from the same bootstrap replica for all scenarios. Finally, we report the percentage changes from the bootstrapped baseline.

The first observation is that the confidence intervals of the reference situation obtained with the objective approach of incidence H, intensity A and measure M cover the values calculated from the survey sample.

Not surprisingly, given the social protection policies considered, all three simulations

Table 3: Multidimensional poverty in Morocco - Situation at 2018 and simulations results

			H			A			M		
			Inf	**Value**	**Sup**	**Inf**	**Value**	**Sup**	**Inf**	**Value**	**Sup**
Randon selection targeting	**Baseline - Survey**		-	0.1930	-	-	0.4267	-	-	0.0824	-
	Simulation 1	**Ponctual values**	0.1843	0.1859	0.1874	0.4221	0.4231	0.4241	0.0781	0.0786	0.0792
		Variation %	-	***-3.71%***	-	-	***-0.86%***	-	-	***-4.53%***	-
	Simulation 2	**Ponctual values**	0.1626	0.1649	0.1671	0.4068	0.4089	0.4110	0.0666	0.0674	0.0682
		Variation %	-	***-14.57%***	-	-	***-4.19%***	-	-	***-18.14%***	-
	Simulation 3	**Ponctual values**	0.1545	0.1572	0.1599	0.4027	0.4050	0.4072	0.0627	0.0637	0.0646
		Variation %	-	***-18.56%***	-	-	***-5.10%***		-	***-22.72%***	-
Objective identification targeting	**Baseline - bootstrap**		0.1325	0.1993	0.2660	0.4253	0.4268	0.4283	0.0565	0.0850	0.1135
	Simulation 1	**Ponctual values**	0.1300	0.1956	0.2611	0.4241	0.4257	0.4272	0.0553	0.0832	0.1112
		Variation %	-	***-1.86%***	-	-	***-0.27%***	-	-	***-2.12%***	-
	Simulation 2	**Ponctual values**	0.1261	0.1896	0.2530	0.4243	0.4259	0.4275	0.0537	0.0807	0.1078
		Variation %	-	***-4.85%***	-	-	***-0.22%***	-	-	***-5.06%***	-
	Simulation 3	**Ponctual values**	0.1237	0.1860	0.2482	0.4231	0.4247	0.4263	0.0525	0.0790	0.1054
		Variation %	-	***-6.68%***	-	-	***-0.50%***	-	-	***-7.14%***	-

Source: Authors based on ENPSF data - 2018

have a positive effect on the A, H and M measures, regardless of the approach chosen. Moreover, the variations obtained under random targeting are all statistically significant since the confidence intervals obtained after simulation do not cover the reference values. In the case of targeting by objective identification, by examining the bootstrap reference confidence intervals and those obtained after simulation, it appears that the variations are statistically non-significant for H and M. This variation is statistically non-significant for the intensity, A in the case of simulation 3 only. This phenomenon occurs because even when a household is no longer deprived on one or more indicators, it can remain poor (H is less impacted while A is reduced). Moreover, the variation in M is only a result of the variations in A and H obtained by differentiation (see Section 2.2).

A priori and logically, a social protection policy should be more effective when it objectively targets the beneficiaries of the reform. However, the relative variations obtained in our case are always greater in absolute values under random targeting than under objective identification. This result, which corroborates the conclusions of Hoddinott (1999), can be explained by the fact that the probit models estimated were done in a context of unbalanced samples for which even good measures of goodness of fit are not reliable.[16] This situation could be frequently observed for the indicators used to calculate the MPI. For example, in the case of Morocco in 2018, six out of 13 deprivation rates are below 10% (Table 2). Thus, when targeting, the use of the objective approach does not seem to clearly dominate the random targeting approach in our analysis.[17]. This result could also be observed because of the homogeneity of deprivate households on each indicator targeted by the reform.

It is clear that the variations recorded under simulation 3 are simply the accumulation of the other two variations (simulations 1 and 2). This is explained by the construction of the MPI, since under each of the simulations, the deprivation status of certain households and individuals goes from 1 to 0 for specific indicators, all other things being equal, for the non-targeted indicators. In other words, in this article no correlation between indicators is taken into account. If this assumption is relaxed by considering other approaches, we may obtain different results due to the potential amplification of deprivation reduction.

5.3.2 Results in stochastic dominance

The ponctual and interval analysis conducted previously depends on the chosen threshold, k. To go beyond the arbitrariness associated with the setting of this threshold, we present the results of the distributional analysis by comparing the distribution of c_i scores for the reference situation with those obtained for the three simulations.

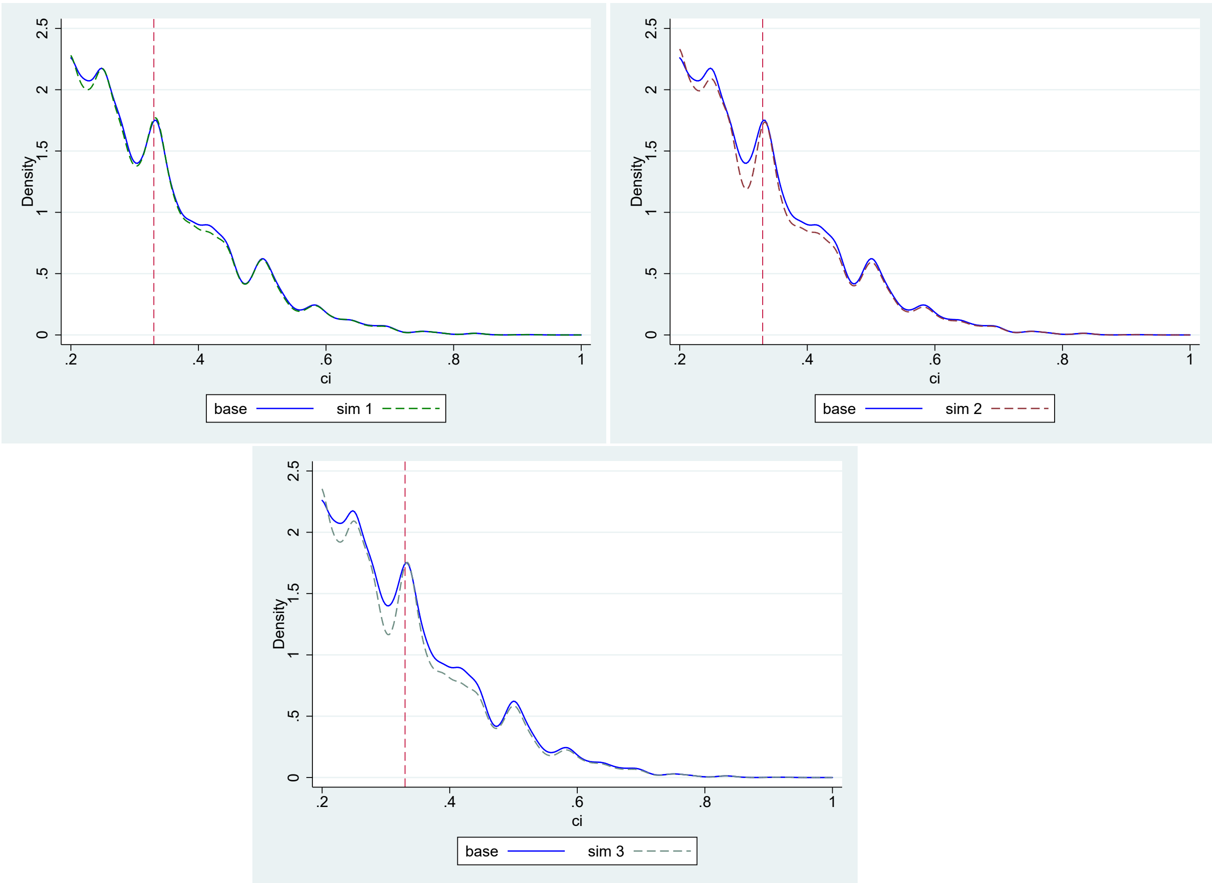
Examination of the density functions taken in pairs shows that, as expected, in each case the simulated curve lies to the left, sometimes weakly, of the reference curve for

[16]For example, for the model relating to deprivation according to the malnutrition indicator, the rate of good classifications at the reference situation is 93.68% but the sensitivity rate is low (0.75%). For the model relating to deprivation according to the schooling indicator, the rate of correct classifications at the reference situation is 89.46% and with a sensitivity rate of 5.52%.

[17]Recall that in Simulations 1 and 3, we retained random targeting even in the objective identification targeting approach for the mortality indicator

all individuals for whom c_i^s decreases whether they are multidimensionally poor or not (Figure 1). Indeed, it is clear that $c_i^s \leq c_i$ for any individual i. We also note that the shift to the left is more pronounced under simulation 2 for the improvement of the deprivation indicator in terms of schooling. The comparison in the case of simulation 3 highlights the effect of the two social policy reforms (health and education) (see Figure 4 in the appendix).[18] The first-order stochastic dominance analysis based on the

Figure 1: Density curves of c_i*



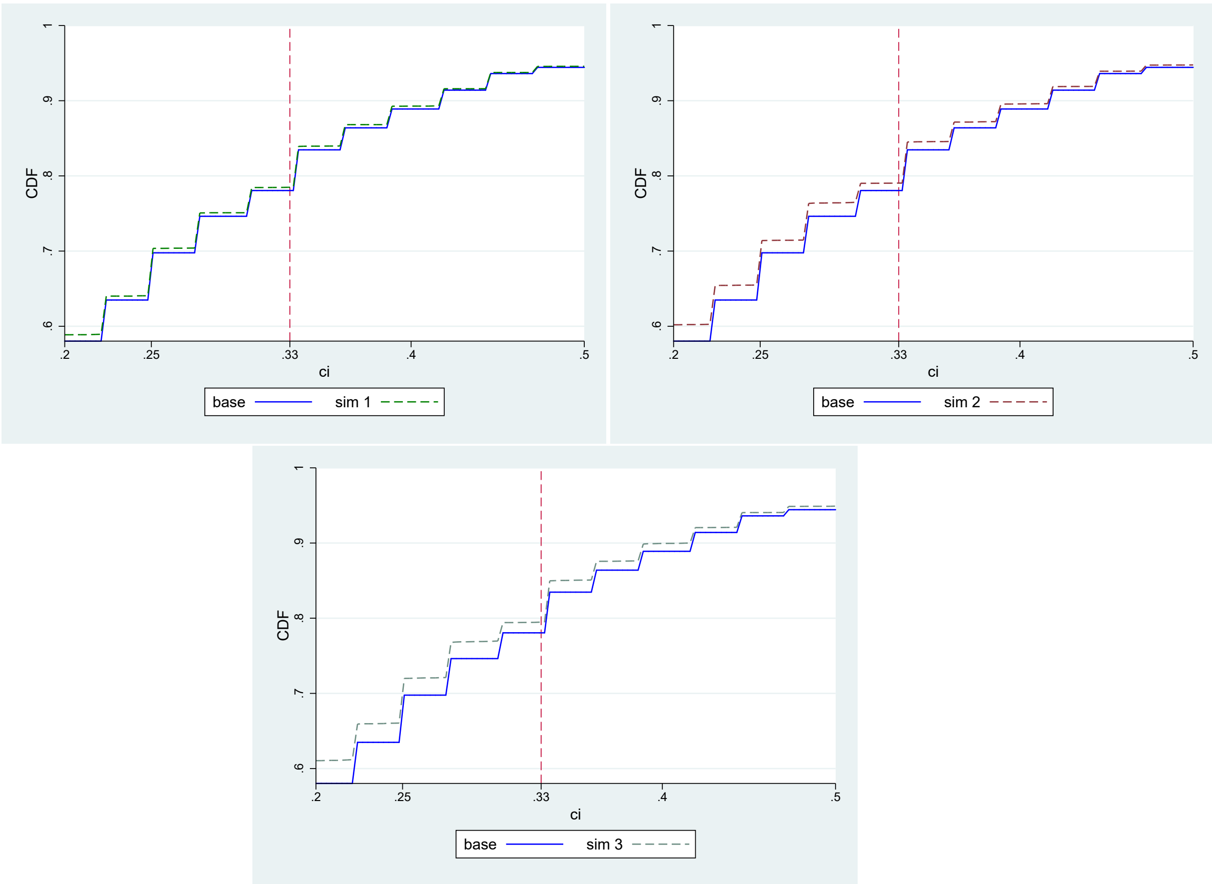
Source: Authors based on ENPSF data - 2018
*The focus is on $c_i > 0.2$ for more clarity.

comparison of the curves of the score distribution functions c_i highlights their staircase shape, which can be explained by the definition of c_i and by the weight accumulations for each individual. This analysis also shows results similar to those deduced previously. The curves representing the simulated cases are systematically to the left of the reference one, hence the first order stochastic dominance. Moreover, the gap between the curves is greater when the reform affects the enrollment indicator (simulation 2) and more when both indicators are impacted (simulation 3) (Figures 2). We also note that the gap

[18] In Figure 4 in the appendix, we present the two distributions over the entire domain of c_i (0 to 1).

between the curves narrows as c_i increases. This is explained by the targeting based on objective identification that is retained for the two deprivation indicators and that favors individuals with the highest probability of not being deprived on each indicator.[19] The last concept used to approach the simulated effects of social protection reform are

Figure 2: Stochastic dominance curves - Order 1*

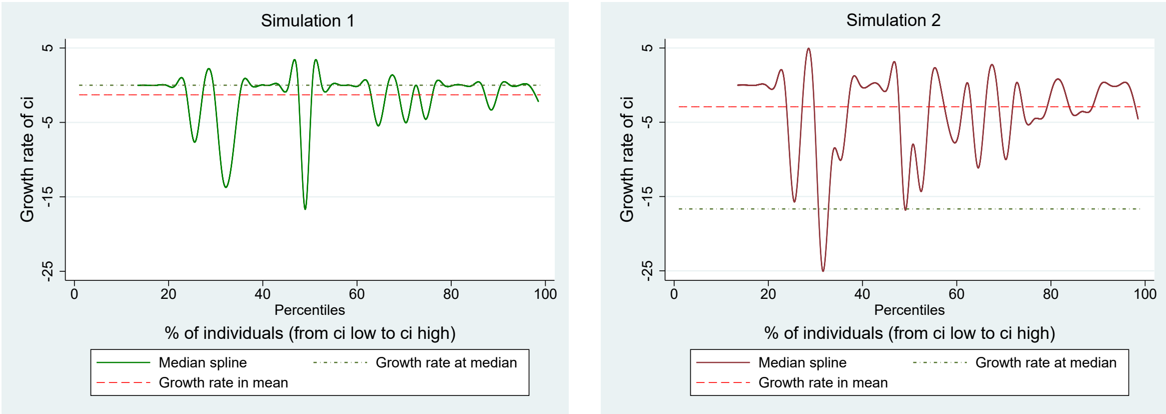


Source: Authors based on ENPSF data - 2018 *Focus is on the $0.2 < c_i > 0.5$ for more clarity.

incidence curves (IC). They were introduced by Ravallion and Chen (2003) in particular to analyze the dynamics of monetary poverty in relation to economic growth and the evolution of inequalities. In our case, these curves give an indication of the impact of the welfare reform on the distribution of the vector of c scores, by comparing the reference situation with a simulated case. Unlike Ravallion and Chen (2003), given the definition of multidimensional poverty based on the vector of deprivation scores c and the threshold k, the reading is inverted. Indeed, the multidimentionaly poor are to the right of the threshold. Thus, the incidence curve is the representation of the relationship between each population percentile and the corresponding growth rate of c_i, between the reference situation and the simulated scenario. The observed growth rates are naturally all

[19] Figure ?? in the Appendix, summarizes this result by comparing the four curves simultaneously.

Figure 3: Reform Incidence Curves - Sim 1 and 2



Source: Authors based on ENPSF data - 2018

negative (Figure ??).[20] The analysis of the incidence curves shows that the least poor individuals would benefit the most from the simulated reforms in terms of the growth rate of c_i. Indeed, for two individuals i and i', both deprived in an indicator j and then targeted by the social protection policy and such that $c_i < c_{i'}$, the percentage change in c_i will be higher than the rate of change in $c_{i'}$. This explains the shape of the associated incidence curves where the rates weaken in absolute value as c_i increases for the same reasons that the gaps decrease between the distribution functions (See Figures 3). [21] Finally, the growth rates recorded are logically higher in absolute terms for simulation 3 than for simulations 1 and 2.

6 Conclusion

The impact analysis of public policies to fight poverty often considers a measure of monetary poverty. The methods used, particularly microsimulation, have become relatively standard. In this article, we approach the impact of the reform of the social protection system in Morocco on multidimensional poverty measured by the MPI introduced by OPHI. To do this, we develop two innovative approaches that differ in the targeting mechanism of the individuals benefiting from the reforms conducted but that can also be used in a complementary manner. The first approach bases the identification of beneficiaries on a random selection among households (and therefore the individuals who are

[20] Two incidence curves relating to simulation 3 are given in the Appendix, one obtained with non-parametric smoothing (Stata's *gicurve* command) and the other constructed from the observed data (See Figures 7).

[21] The c_i of non-deprivate individuals on all dimensions or non-deprivate individuals on the indicators affected by the reform do not change, which explains the zero growth rates. It is also possible that the c_i of some deprivate individuals on one or other of the indicators targeted by the policy remain constant if these individuals did not benefit from the reform.

members of these households) that are deprivate on each of the indicators considered. The second, more objective method relies on a probabilistic model (probit) to identify households that change status from deprivate to non-deprivate on a given indicator. The probabilities predicted by this model are related to the characteristics of the households and are adjusted by residuals, as proposed in the theory in this context. These two methods can be used regardless of the number of indicators impacted by the reforms to be undertaken.

In the empirical part, we identify the intersections between the contents of social protection systems, the dimensions and the indicators used in the construction of the MPI. Based on the recommendations of the *Assises nationales de la protection sociale* in Morocco, which are currently being implemented, we have selected three target indicators, two related to health and one related to education.

In addition to the usual ponctual analysis, we construct simulated confidence intervals (Monte Carlo and bootstrap) for the multidimensional poverty measures and then perform a distributional analysis (density functions, distribution functions and incidence curves) to overcome the arbitrariness of the threshold setting associated with these measures and make robust comparisons.

In our application, we use data from the *Enquête Nationale sur la Population et la Santé Familiale* (ENPSF) of 2018 to measure and approach the impact of social protection reforms on multidimensional poverty in Morocco. We demonstrate that both proposed approaches are relevant in this context. Examination of the results shows that targeting by objective identification does not necessarily dominate random targeting for the simulations we conducted. However, this finding cannot be generalized since this result can be explained by the fact that the probit produced the targeting probabilities was estimated on a highly unbalanced sample or by the high homogeneity of deprivate households. Indeed, the deprivation rates in the indicators considered are low at the baseline. It should also be remembered that in the targeting approach by objective identification, only deprivate households on the indicator considered can see their status on this indicator change from 1 to 0 whether or not they are poor in the multidimensional sense. It is also possible that the random identification method does not give different results from those obtained by objective identification if the targeted individuals have similar poverty profiles.

Moreover, in both cases and as expected, the variations obtained by cumulating programs are greater in absolute values than those obtained on each of the reforms taken individually. Another interesting finding arises from an examination of the results for H, A and M. Indeed, with the implementation of the social protection reforms, deprivations according to the targeted indicators may decrease for some households (A is impacted) but leave the incidence of multidimensional poverty (H) unchanged. The distributional analysis confirms these results. It should be added that this entire approach can be conducted by area of residence, by region, or for any other group of interest.

Finally, it should be noted that all the results obtained with the two methods developed in this article are based on the hypothesis of independence of the effects on the indicators (under the principle of "*all things being equal*"). This assumption may not always be plausible since correlations between indicators may exist. In this case, our approaches would have to be adjusted to incorporate these correlations in order to refine the evaluation of the impact of the social protection reform, which would be more important.

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Annexes

Table 4: Revised Arab IPM Framework - Original and Morocco

Household is considered multidimensionally poor if its total deprivation score >20%					
Pillar and weight assigned	**Dimension**	**Indicator and weight within Dimension**	**Deprived if**	**Original Weight**	**Morocco 2018**
Social or capability well-being (weight=50%)	**Health and Nutrition (weight =50/2 = 25%)**	Child mortality (weight=1/3)	Any child in the household died before the age of 5 during the past 10 years.	25/3	25/3
		Child nutrition (weight=1/3)	Any child (0-59 months) is stunted (height for age < -2) or any child is underweight (weight for age < -2).	25/3	25/3
		Early pregnancy (weight=1/3)	Any women aged 15-24 in the household gave birth before the age of 18.	25/3	25/3
	Education (weight =25%)	School attendance (weight=1/3)	Any child in the household aged 6-17 is not attending school and has not completed secondary education.	25/3	2*25/3 = 50%/3
		Age schooling gap (weight=1/3)	Any child aged 8-17 is enrolled at two grades or more below the appropriate grade for their age.	25/3	**0**
		Educational attainment –18+ (weight=1/3)	All household members aged 18+ have not completed secondary education.	25/3	25/3
Living standards or material well-being (weight= 50%)	**Housing (weight = 50/3 = 16.67%)**	Overcrowding (weight=1/2)	The household has three persons or more, aged 5+ years, per sleeping room.	16.67/2 = 25/3	25/3
		Type of dwelling (weight=1/2)	The housing situation fits at least one of the following conditions: (i) home is a place other than a standalone house or apartment; (ii) it has a non-permanent floor; or (iii) it has a non-permanent roof*	16.67/2 = 25/3	25/3
	Access to services (weight =16.67%)	Improved drinking water (weight=1/3)	The household does not have any of the following sources: piped water into a dwelling, piped water into a yard, or bottled water.	16.67/3 = 50/9	50/9
		Improved sanitation (weight=1/3)	The household does not have access to improved sanitation or it is improved but shared with other households**.	16.67/3 = 50/9	50/9
		Electricity (weight=1/3)	The household does not have access to electricity.	16.67/3 = 50/9	50/9
	Assets (weight =16.67%)	Communication assets (weight=1/3)	The household has no phone (mobile or landline), television or computer.	16.67/3 = 50/9	50/9
		Mobility assets (weight=1/3)	The household has no car/truck, motorbike or bicycle.	16.67/3 = 50/9	50/9
		Livelihood assets (weight=1/3)	The household has no fridge, washer, any type of heaters, or any type of air conditioning/cooler.	16.67/3 = 50/9	50/9

Source: adapted from (ESCWA, 2017) by the authors.

* Non-permanent floor includes earth, sand, dung or rudimentary (wood planks/bamboo/reeds/grass/canes). Non-permanent roof includes the roof being unavailable or made of thatch, palm leaf, sod, rustic mat, palm, bamboo, wood plank or cardboard.

** Improved sanitation facilities in line with the WHO and UNICEF JMP guidelines includes flush/pour flush to piped sewer system, septic tanks or pit latrines; and ventilated improved pit latrines, composting toilets or pit latrines with slabs.

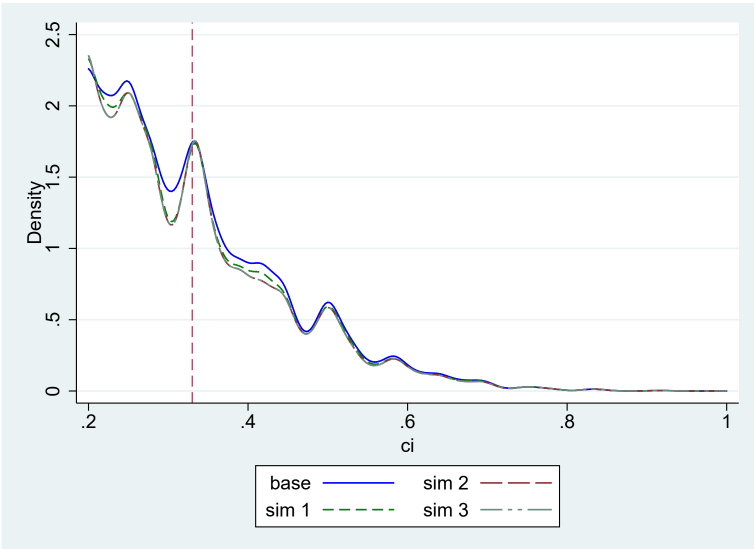
Note: In our case, given the modalities of the toilet type variable in the survey, we considered a household to be non-deprivate on the indicator "Improved sanitation" when it has a toilet with a drain connected to the sewer or not, or a toilet without a drain connected to the sewer, and these toilets are not shared with other households.

Table 5: Descriptive statistics of the variables used in the objective approach - Probit model

Variable		**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Frequency %**
Age - Hous. Head		67,412	52.55	13.69	16	98	
Hous. size			5.60	2.60	1	25	
Wealth Score			33,898.10	19,570.93	4.14	67,792.09	
Area	**Urban**						61.27
	Rural						38.73
Gender - Hous. Head	**Male**						89.11
	Female						10.89
Education lever - Hous. Head	**None**						46.16
	Undergr.						25.59
	College						11.41
	Secondary						9.23
	Superior						7.61
Marital status	**Single**						2.46
	Married						87.99
	Widower						7.47
	Divorced						1.64
	Separed						0.43

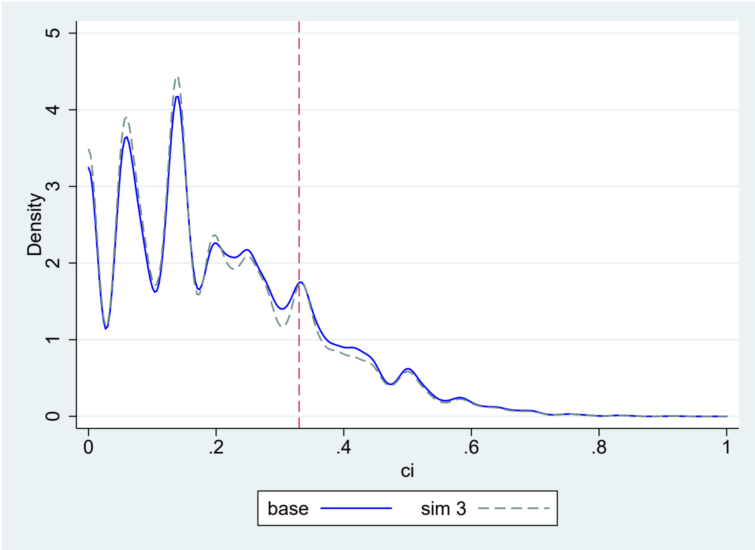
Source: authors from ENPSF - 2018.

Figure 4: Density curves - 4 curves



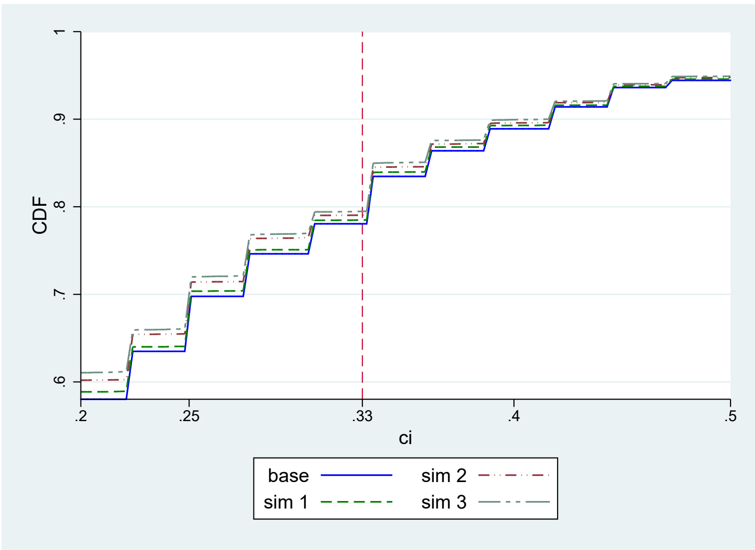
Source: Authors based on ENPSF data - 2018

Figure 5: Density curves - Full range



Source: Authors based on ENPSF data - 2018

Figure 6: Stochastic dominance curves - Order 1 - Global



Source: Authors based on ENPSF data - 2018

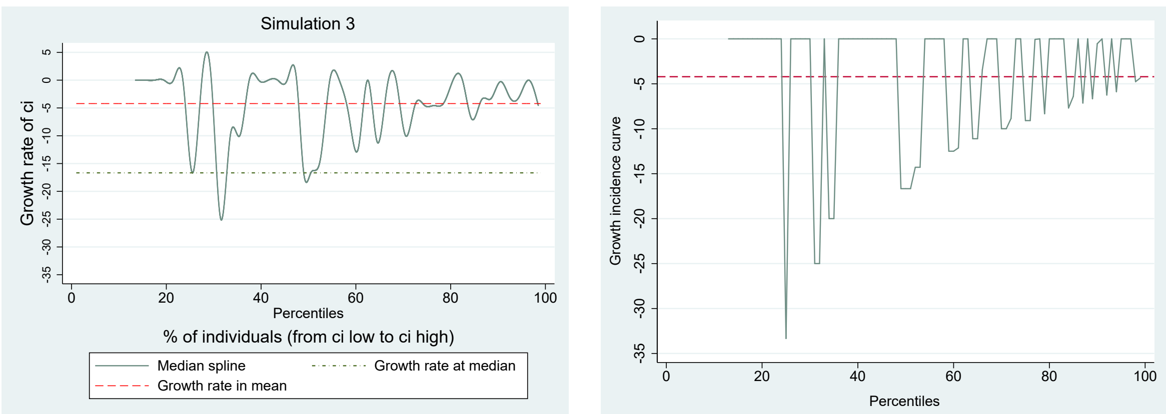
Table 6: Growth rate of c_i in % per percentile (between baseline and simulations)

	SIM1	SIM2	SIM3
Growth rate of the average	-1.29	-2.92	-4.21
Growth rate at median	0.00	-16.67	-16.67
Average growth rates	-1.19	-3.11	-3.74

Percentiles	Growth rate		
	SIM1	SIM2	SIM3
10	0.00	0.00	0.00
15	0.00	0.00	0.00
20	0.00	0.00	0.00
25	-0.61	-1.26	-1.33
30	-0.51	-1.05	-1.11
40	-1.51	-3.03	-3.08
50	-1.54	-3.09	-3.13
60	-1.28	-3.47	-3.78
70	-1.40	-3.43	-3.92
80	-1.34	-3.46	-4.00
85	-1.26	-3.35	-3.93
90	-1.26	-3.32	-3.87
95	-1.20	-3.14	-3.80

Source: Authors based on ENPSF data - 2018

Figure 7: Reform Incidence Curves - Sim 3



Source: Authors based on ENPSF data - 2018

Proposition 1. *Let c_i^0 and $c_{i'}^0$ the scores of individuals i and i' at the baseline. Suppose that i and i' are both deprivate on indicator j. If $c_i^0 < c_{i'}^0$ and i and i' are both targeted by the welfare reform on j then all else equal, $\hat{c_i} > \hat{c_{i'}}$ where $\hat{c}$ is the rate of change in c between the baseline and post-reform situations.*

Proof. Knowing that $c_i^0 = \sum_{j=1}^{d} w_j g_{ij}^0 \quad \forall i = 1, 2, ...n$ (Equation 1) and that $g_{ij}^0 = g_{i'j}^0 = 1$ at the reference situation and $g_{ij}^1 = g_{i'j}^1 = 0$ after the reform affecting the indicator j, then $\hat{c_i} = -\frac{w_j}{c_i^0}$ and $\hat{c_{i'}} = -\frac{w_j}{c_{i'}^0}$ and therefore $\hat{c_i} > \hat{c_{i'}}$. □