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Static and Dynamic Comparison of Monetary and Non-monetary Multidimensional Poverty: Evidence from Morocco

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This paper compares monetary and non-monetary poverty in Morocco from 2013 to 2019 using Enquete Panel des Ménages (EPM) data. It finds that while the incidence of poverty has fallen substantially during this period, there exists an important mismatch between both measures that is not resolved when taking a dynamic lens. On a static level, while displaying similar headcounts, the two measures identified different populations as poor and had different poverty determinants. Taking a dynamic lens, we find that the level of mismatch between the two measures does not improve: Despite similar levels of mobility, transitions in poverty status in one measure are not accompanied by simultaneous transitions in the other measure. We thus suggest the concomitant use of both monetary and multidimensional measures when targeting the poor.

1. INTRODUCTION

Poverty has traditionally been measured through the lens of a monetary measure, be it income or consumption. While the monetary approach is still considered the "gold standard" (Sumner, 2007) of poverty measurement for development organisations such as the World Bank, an important body of literature has pointed to the limitations of this approach, favouring alternative, non-monetary measures.

Indeed, the monetary approach has been criticised for having unrealistic assumptions since it posits that individuals behave as rational agents driven by utility maximisation (Johannsen, et al. 2007). Empirical investigations have found on the other hand that scarcity can turn individuals into irrational agents by reducing their cognitive capacities (Mullainathan and Shafir, 2013). It also holds that individuals have homogenous preferences (Thorbecke, 2007) that exclude any socio-cultural or personal variation, and that utility only stems from market goods, thus ignoring any non-market externalities (Bourguignon and Chakravarty, 2003). In addition, Clark and Hulme (2005) and Spicker (2007) argue that the monetary approach, being based on changing flows (consumption and income) does not account appropriately for the chronicity of poverty. Finally, numerous studies have pointed to measurement errors in the monetary approach, notably when it comes to income (Evans, 2020).

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The quest for alternative measures, while started early (Rowntree, 1902), received more attention with the pioneering work of Amartya Sen (1979, 1985, 1999), defining the capability approach. Non-monetary measures derived from this approach have been deemed more realistic and direct (Kuklys & Robeyns, 2004), leaving room for socio-cultural variations as well as non-market externalities, notably governments' interventions (Thorbecke, 2007). From research to practice, numerous measures of non-monetary poverty have emerged, amongst which are the multidimensional poverty index (MPI) followed by the Alkire-Foster methodology (Alkire & Foster, 2011). The latter is now used by the UNDP as an alternative measure for poverty, and multiple countries have resorted to this methodology to create "national MPIs".

However, given the fundamental differences in both approaches, one might expect large discrepancies in identifying the poor. Indeed, a growing body of literature has investigated the mismatch between monetary and non-monetary poverty and its policy implications. Some studies have compared macro-level trends to determine that a reduction in monetary poverty does not necessarily lead to an improvement in non-monetary dimensions (Bourguignon, et al. (2010); Alkire & Santos (2014)), while others have focused on cross-country comparisons (Drèze & Sen, 2013). However, the most compelling evidence comes from studies using the same survey dataset from a particular country to compare monetary and non-monetary poverty. Perry (2002) finds a 60 percent average mismatch in OECD countries which means that 60 percent of non-monetary poor would not be identified as poor with an exclusively monetary approach. Similar studies with a focus on developing countries have come to the same conclusion: Alkire & Shen (2017) found a 75.4 percent exclusion error in China, while Salecker, et al. (2020) in Rwanda & Levine, et al. (2012) in Uganda & Klasen (2000) in South Africa find exclusion rates of 47.5 percent, 44 percent, and 30 percent respectively. Moving further to subgroup analysis, researchers have uncovered major differences in poverty risk for both approaches: non-monetary and monetary poverty do not affect the same sub-populations with regards to ethnicity, geography, and household characteristics (household size, education of household head…).

It is to be noted that the bulk of these empirical investigations have taken place in a static setting. While the mismatch uncovered is important, one might argue that it might be reduced by switching to a dynamic setting and accounting for poverty chronicity. This argument may hold theoretically, as non-monetary measures of poverty tend to be "stocks", in contrast with "flow" monetary variables. Dynamic comparisons of monetary and non-monetary poverty are rare due to the scarcity of panel data, but a few studies have tried to tackle the subject, mostly in OECD countries. For example, Whelan et al. (2004) analysed European panel data to find that there is a stronger correlation between monetary and non-monetary poverty in a dynamic setting, while the level of mismatch is equivalent. Suppa (2016), analysing German panel data, has found that only 34.17 percent of the chronic multidimensional poor (using a non-monetary index) are also chronic monetary poor: the static mismatch between both measures was not improved when taking a dynamic lens. He also found similar transient poverty rates for both measures (20 percent), which may invalidate the hypothesis of non-monetary measures inertia.

Even fewer studies have taken place in poor and developing countries, where poverty is endemic, and usually measured differently, through an absolute approach. Pioneering this field, Baulch & Masset (2003) have found considerably more persistence in education and health deprivations compared with income poverty when studying 1990 Vietnam, however, this study did not use a non-monetary index to account for all dimensions of non-monetary poverty at once. Using Ethiopian panel data, Seff & Jolliffe (2016) found slightly more volatility for consumption poverty compared to multidimensional poverty (using a non-monetary index). Contrary to Whelan, et al. (2004), they found an even lower correlation between both measures when considering panel data: 53 percent of those whose multidimensional poverty index improved, saw their consumption worsen. Tran, et al. (2015) also found that a dynamic comparison of both measures in Vietnam reveals comparable volatility rates and no improvement in the mismatch. Other studies include Bruck & Kebede (2013) and Alkire & Fang (2018) (for a survey, (see Azami, 2021).

This study aims to contribute to the literature on the mismatch between monetary and non-monetary poverty, using a static and dynamic lens. Using panel data from Morocco, we investigate and compare the drivers between both forms of poverty, for different population subgroups over time. Given the dearth of panel data in developing countries, few empirical investigations have addressed this knowledge gap (Alkire, 2018), and we believe that the conclusions drawn from Morocco's case may be generalised to similar countries.

Indeed, Morocco might constitute a good proxy for other middle-income countries with similar growth rates, and gradual improvements in monetary and non-monetary poverty. Despite being dependent on mainly rainfall-based agriculture, it has been able to sustain a moderate average annual growth rate of 4.2 percent during the past two decades. These economic gains have translated into lower monetary poverty rates, lifting nearly 1.7 million people out of poverty between 2007 and 2018 (High Commission for Planning, 2020), and effectively eradicating extreme poverty as defined by the World Bank (1.25 $/day). Monetary poverty (as defined by a national poverty line) is however still important for certain subgroups: rural areas, women and some inland regions are particularly prone to it. Meanwhile, important improvements in non-monetary dimensions have also been achieved, with child mortality rates going from 47 per 1000 to 22 per 1000 live births between 2003 and 2018, while preschool enrollment went from 45.6 to 62.1 percent between 2016 and 2019 (High Planning Commission, 2020). Given the important improvements in different forms of deprivations, it will be of prime interest to analyse whether the dynamics and patterns of monetary and non-monetary poverty were similar, and whether they concerned the same population subgroups.

What policy implications could be drawn from such a comparison here? We argue that four policy implications would ensue. First, if we hold that non-monetary measures present a more direct profile of poverty, it is difficult to accept monetary measures as a valid proxy. Indeed, it would have a detrimental effect on targeting with sizeable exclusion errors for the non-monetary poor but monetary non-poor. It would also allow for a sizeable inclusion error for the monetary poor but not the non-monetary poor. These errors can be high with up to 75.4 percent exclusion error in China (Alkire & Shen, 2017) leading to misdistribution of resources: 30 percent of multidimensional poor not receiving any government subsidy (Alkire & Shen, 2017).

Second, using monetary measures only might prove problematic to assess government policies, since they do not necessarily account for publicly provided goods such as health and education. Indeed, Mitra (2016) finds that in Nepal, using consumption only as a proxy for poverty would not have acknowledged important improvements for non-monetary dimensions in the mid-western and far-western regions: these regions had benefited from important poverty alleviation policies post-civil war.

Third, why should we accept a proxy if we can construct a more direct measure of poverty from the same dataset? Indeed, all included literature has managed to produce both monetary and non-monetary measures from the same survey data.

Finally, if we accept income or consumption as poverty dimensions in their own right, we must acknowledge their inherent differences with non-monetary measures. Targeted policies for each type of poverty should thus follow: the monetary poor could for example benefit from cash transfer policies, while the non-monetary poor would be keener on structural long-term change pertaining to their health and education situation.

To compare monetary and non-monetary poverty over time, we use the ONDH (National Observatory for Human Development) panel dataset, which follows a sample of nationally representative households over 4 waves (2013, 2015, 2017, and 2019). Given that information, health, education, and household conditions are collected, we were able to draw on the Alkire-Foster methodology (Alkire & Foster, 2011) to create a specific multidimensional poverty index. On the other hand, monetary poverty is accounted for through consumption figures.

This paper is structured as follows: the first part introduces the topic, while the second part presents the panel data and the strategy followed to analyse it. The third part reports results for the mismatch between monetary and non-monetary poverty, in a static and dynamic setting. Finally, the fourth part concludes with key policy recommendations, study limitations, and key areas for further research.

2. DATA

This paper uses panel household data (Enquete Panel des Ménages, EPM) for four periods (2013, 2015, 2017, 2019) assembled by The Moroccan National Observatory for Human Development (ONDH). The EPM is the first longitudinal survey to be collected in Morocco and one of the very few in the MENA region (Cottin, 2019) and thus provides us with a unique perspective on poverty dynamics.

Although ONDH started collecting data a year prior, we do not use the 2012 wave in our analysis given the significant changes brought to the questionnaire later. Using a three-stage sampling strategy based on official census data, 8000 nationally representative households were selected (Teto & Elhadri, 2018). Collected data include household demographics, level of education, employment, access to health services and health insurance, child mortality, assets, household consumption, and living conditions. An additional 8000 households were added to the panel in 2017 to improve the panel's representability and account for attrition: 2017 and 2019 are thus representative at the regional level as well and present with a higher cross-sectional population, as we can see in Table 1.

Table 1

Cross-sectional and Panel Population Count by Wave

Wave	Cross-sectional		Panel	
	Households	Individuals	Households	Individuals
2013	7755	37246	6329	24620
2015	7999	37218	6329	24620
2017	15828	69215	6329	24620
2019	16879	71798	6329	24620

Note: Panel Individuals count excludes cohabitants, splitting households and 2017'added populations.

It is to be noted that cross-sectional populations include co-habitants, which explains the higher number of individuals with each passing wave (Teto & Elhadri, 2018). In addition, an effort was made to track down individuals who went on to form new households for marriage or work reasons (Teto & Elhadri, 2018). However, we only consider panel individuals and panel households when comparing monetary and non-monetary poverty in a dynamic setting, which when accounting for attrition and ignoring cohabitants and added populations amounts to 24,620 individuals living in 6329 households spanning all four waves. Attrition rate spanning all four waves is 19.3 percent and attrition weights (based on propensity scores) were applied to keep the panel representative.

3. ANALYTICAL STRATEGY

This paper attempts to compare monetary and non-monetary measures of poverty using consumption per capita levels and a multidimensional measure of poverty based on the Alkire Foster methodology (Alkire & Foster, 2011). First, both measures are compared in a static setting across different sub-groups, probing any mismatch in poverty identification and differences in poverty risk factors. We then move to a dynamic setting, considering a panel of individuals over 4 time periods to compare poverty transition profiles and underlying determinants.

(a) Identification of the Monetary Poor

Although income is reported in ONDH surveys, this study uses consumption instead as the monetary indicator of poverty for two reasons. First, consumption was found to be more reliable than income (Deaton, 1997), especially in agriculture-based economies like Morocco where self-employment is important (Haughton & Khandker, 2009). Second, the national poverty line in Morocco is set by the High Planning Commission (HCP) against consumption levels and is used in targeting poor populations for subsidy programmes: any policy recommendations stemming from this paper would thus be more relevant if using consumption as an indicator.

To produce its poverty lines, the HCP first determines the minimum calorie requirement for an individual to live and then transforms it into a basket of minimal foodstuff, which corresponds to a food poverty line. Finally, a non-food poverty line is determined by fitting a model of almost ideal demand to the latest household consumption survey and differentiating urban and rural dwellers (Ezzrari, 2011).

By adding up the food and non-food poverty lines, the HCP produces two distinct absolute poverty lines for rural and urban milieus: these were 4667 MAD per year per capita in urban areas and 4312 MAD per year per capita in rural areas in 2014 (HCP and World Bank, 2017). Using OECD PPP equivalence rates (OECD, 2021), we find that these correspond to a 3.22$ per day per capita for urban areas and 2.97$ per day per capita for rural areas, which approaches the 3.2$ a day World Bank standard for lower-middle-income countries (countries with GNI per capita comprised between 1026USD and 3995 USD in 2019 (World Bank, 2020)) but is far from the 5.5$ a day standard for upper middle-income countries (GNI per capita between 3996 USD and 12375 USD, (World Bank, 2020)), a group which Morocco, with a GNI per capital of 3200 USD in 2019 (World Bank, 2019), is aspiring to join.

Following World Bank procedures, the HCP also produces vulnerability lines, which correspond to 1.5 times the poverty lines (Ezzrari, 2011). These, along with the 2014 poverty lines were actualised using the HCP annual consumer index. As we can see in Table 2, Official Poverty Lines consistently hover around the 3.2USD a day standard (higher for urban areas and lower for rural areas) while vulnerability lines approach the 5.5 USD a day standard but are consistently lower than it and thus might prove a better fit for a country like Morocco.

Table 2

Consumer Price Index and Actualised Poverty Lines by Wave

	2013	2014	2015	2017	2019
Consumer Price Index	112.9	113.4	115.2	117.9	120.4
Poverty line (Urban)					
In MAD (Annual)	4646.4	4667	4741.1	4852.2	4955
In USD PPP (Daily)	3.34	3.22	3.25	3.30	3.42
Poverty line (Rural)					
In MAD (Annual)	4292.7	4312	4380.4	4483	4578.1
In PPP USD (Daily)	3.09	2.97	3.01	3.05	3.16
Vulnerability line (Urban)					
In MAD (Annual)	6969.6	7000.5	7111.65	7278.3	7432.5
In USD PPP (Daily	5.01	4.83	4.88	4.95	5.13
Vulnerability line (Urban)					
In MAD (Annual)	6439.05	6468	6570.6	6724.5	6867.15
In USD PPP (Daily)	4.64	4.46	4.52	4.58	4.74

Notes: The author's calculation is based on the national Consumer Price Index (HCP) with 2014 as a base year and OECD Purchasing Power Parity data.

(b) Identification of the Multidimensional Poor

Given the consensus on the multidimensionality of poverty one of the main challenges of identifying the non-monetary poor lies with selecting poverty dimensions and aggregating those (Ruggeri Laderchi, et al. 2003). Following the work of Sen (1985), many attempts have been made to define universal dimensions critical to well-being (Nussbaum, 2000). There is however a limit to generalisation and Alkire (2002) argues for reasonable adaptation for time and place. In addition, aggregation of said dimensions in an index is not straightforward given the heterogeneity of poverty indicators. Besides, juxtaposing each dimension in multiple dashboard measures would not solve the problem as it decreases international comparability and political buy-in (Ruggeri Laderchi, et al. 2003).

The Alkire-Foster methodology used in this paper, offers some responses to these challenges in identifying the non-monetary poor, by assigning normalised deprivation scores and equal weights to each poverty indicator. It has been used by the Oxford Poverty and Human Development Initiative (OPHI) and the United Nations Development Programme (UNDP) as the basis for the Global Multidimensional Poverty Index (GMPI) (Alkire and Jahan, 2018).

(i) *Dimension, Indicators, Deprivation Cut-offs and Weights*

The non-monetary multidimensional poverty measure developed in this paper is adapted from the GMPI with some adjustments due to data availability and Morocco's specific context. Indeed, in its guidelines for defining a national MPI, OPHI insists that both data constraints and the domestic development agenda should be taken into consideration. Hence, the normative choices for dimensions and indicators should reflect important national development policies while international development objectives such as the SDGs should also be considered (OPHI, 2019). As this is not the first attempt to define a national multidimensional poverty index in Morocco, we also refer to the High Planning Commission's (HCP) measure in our further analysis (HCP, 2020).

Our measure assumes households as the main unit of analysis given that individuals usually pool resources and are impacted by other household members' deprivations (Alkire & Jahan, 2018). Thus, if one individual is deprived in an indicator then everyone in the household is considered deprived in that indicator.

Like the GMPI, our measure comprises 3 dimensions, namely Education, Health, and Living Conditions. This section delves into each dimension's selected indicators of deprivation (see Table 3 for a summary).

Health

We chose three indicators for health deprivations, namely "Child Mortality", "Effective Access to health services" and "Health Insurance Coverage".

According to the GMPI, "Child Mortality" concerns households in which a child (defined as any individual who has not reached 18 years old) has died during the 5 years preceding the survey (Alkire and Jahan, 2018). However, the EPM questionnaire only includes deaths of children aged up to 5 years during the past 5 years, we thus use this definition for our "Child Mortality" indicator.

Besides "Child Mortality", the GMPI also uses "Nutrition" as an indicator with deprivation defined as having a body mass index below an age-specific cut-off. Given the lack of anthropometric data in the EPM panel and Morocco's specific case, we use "Effective Access to Health Services" and "Health Insurance Coverage" instead.

"Effective Access to Health Services" assesses whether an individual had access to health services when in need during the 4 weeks preceding the survey. The EPM questionnaire also asks about reasons behind not having access to health services, and we assigned a deprivation status accordingly: if the individual has not had access because of costs or remoteness, they were deemed deprived. Individuals with benign afflictions or who did not seek a health consultation because of personal choices (no female or male doctor present, do not like to consult) were assigned a non-deprived score. The inclusion of this indicator is in line with SDG target 3.8 “access to quality essential healthcare services” (Alkire and Jahan, 2018). In addition, it is included in multiple national MPIs, notably in middle-income countries: Panama, Pakistan, Vietnam, and the Dominican Republic (Santos, 2019)

“Health Insurance Coverage” assigns a deprivation status if any eligible household member is not covered by a health insurance scheme. The EPM questionnaire asks about non-coverage reasons and thus allows us to exclude individuals who chose to forego insurance coverage by their own choice.

The inclusion of this indicator is justified on many grounds. First, universal health insurance coverage is a major development policy of Morocco’s government. Indeed, starting in 2002, Morocco instituted two basic public health insurance schemes: the first, AMO (Assurance Maladie Obligatoire), targets all working population, while the second, RAMED (Régime d’Assistance Médicale) is aimed at the poor and near-poor population (2 million households) (Cottin, 2019). RAMED’s roll-out only started in 2012, and thus, it will be interesting to assess multidimensional poverty dynamics in this regard. Second, the inclusion of this criteria is also in line with SDG target 3.8 “Achieve universal health coverage” and it has become a fixture of multiple national MPIs, notably in Mexico, Chile, Moldova, and Vietnam (Santos, 2019).

Education

Similar to the Global MPI (GMPI), our study uses “School enrollment” and “School attainment” as the two indicators for the education dimension.

“School enrollment” in the GMPI assesses whether individuals aged 6 to 14 (6 years old and 14 years old being included) are currently attending school. This requirement is similar to Moroccan national education standards (Law 04-00 of Dahir 1-00-200, May 19th, 2000) which institutes compulsory education for all children aged 6 to 14, assorted with penalties for parents who fail to comply.

“School attainment” looks at education achievement within the household. Deprivation is defined as having no household member attaining 6 years of formal education. Alkire and Santos (2014) argue that years of schooling are a proxy for literacy and understanding of information, 6 years being the usual length of primary education globally. While there is no formal definition of literacy in terms of school attainment in Morocco, primary education also spans 6 years, we will thus use the same indicator.

Living Conditions

Similar to the GMPI, we chose “Electricity”, “Water”, “Sanitation”, “Housing”, “Cooking Fuel” and “Assets” as living conditions indicators of poverty.

A household is deprived of “Electricity” if it does not have access to an electricity source be it on-grid or off-grid. This is in line with SDG 7.1.1 (Alkire & Jahan, 2018) and reflects the importance of electrification on Morocco’s development agenda.

Deprivation in "Water" is defined as not having access to improved water or having to walk more than 30 minutes round-trip to the nearest improved water source. The 30 -minute round-trip limit is less strict than national guidelines, which are defined by the HCP in terms of distance (200 meters in urban areas and 1km in rural areas) (HCP, 2020), but given the EPM questionnaire formulation, we opt for the international standard.

Deprivation in "Sanitation" is defined as not having access to improved sanitation which here refer to a water closet or having to share the facilities with another household. While SDG guidelines refer to various kinds of improved sanitation (latrines, ventilated improved pits, composting toilets, (see Alkire & Jahan, 2018), EPM data only reports on water closets.

The "Housing" indicator refers to the house's building materials, namely for roof, walls, and floor. Similar to the GMPI and following SDG guidelines, a household is deemed deprived if at least one of the latter is composed of inadequate materials (namely a floor made of mud, clay, or sand; or roof/walls using natural materials such as thatch or mud). This goes further than HCP's measure which only considers flooring for this indicator (HCP, 2020).

The "Assets" indicator considers a household deprived if it does not own strictly more than one of "small assets" (motorcycle, refrigerator, TV, phone, or computer) and does not own a "big asset" (car, truck, or tractor). This approach differs slightly from the GMPI and HCP measures which include bicycles in "small assets", given that EPM data does not report on such assets. While no SDG refers to this indicator, its inclusion is relevant given its important relationship to multiple capabilities (Santos, 2019).

Following the GMPI methodology, all three dimensions are assigned equal weights of 1/3, and indicators of the same dimension are assigned equal nested weights (see Table 3).

(ii) ***Association among Indicators***

To evaluate the adequacy of a multidimensional measure, it is interesting to look at the association between indicators, probing for redundancy

We first calculate Cramer's V values [1]indicating associations between every pair of indicators in 2013 (Table A1, Appendix). Following Akoglu (2018), we consider that an association is weak if presenting with a value below 0.1, moderate if between 0.1 and 0.25, and strong if superior to 0.25. As we can see in Table A1, most of the association are weak. Indicators within the same dimension also tend to be weakly to moderately associated, adult literacy and child schooling deprivations only present with a 0.13 Cramer's V, and all pairs of health indicators show weak associations.

The only strong association observed is between Electricity and Assets, which might be explained by the important number of electric devices included in the "small assets" category (computer, phone, refrigerator, TV) and also by the overall low headcounts of both deprivations (see Figure 2).

Following Tran, et al. (2015) we then compute a redundancy ratio equal to the percentage of deprived individuals in two indicators divided by minimum the raw headcount ratio of said indicators. Ranging from 0 to 1, with 1 indicating total overlap and 0 complete mismatch. Table A2 (appendix) presents the redundancy ratio in 2013 for all pairs of indicators

[1] Cramer's V values measures the strength of association between two discrete variables. It is based on the Pearson's Chi-squared test (Cramer, 1946).

Table 3

Dimensions, Indicators, Cut-offs, and Weights

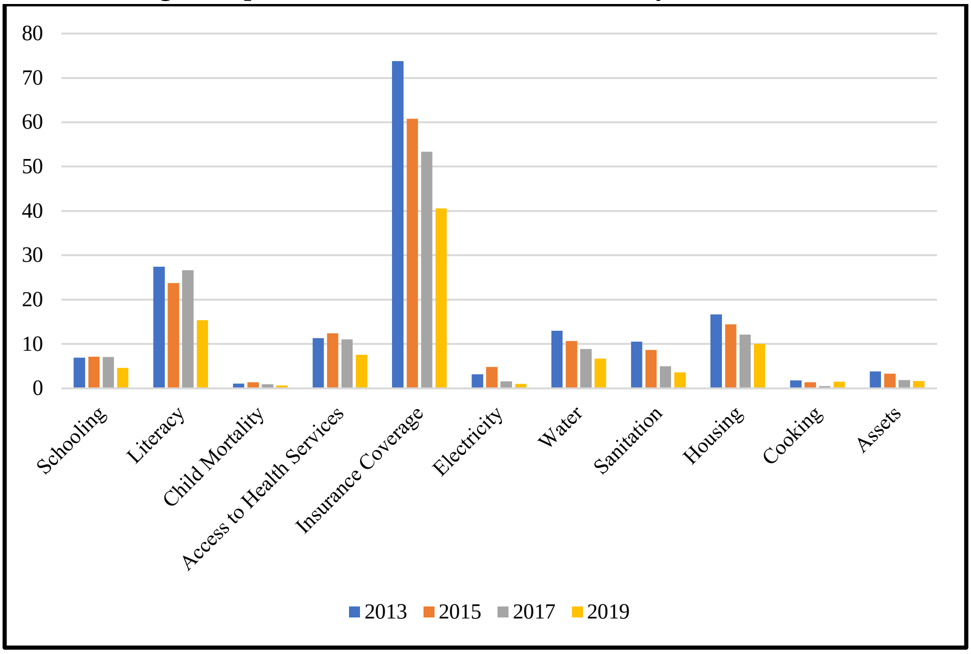
Dimensions and Indicators of Poverty	All Household Members are Considered Deprived if…	Weight
Health		
Child Mortality	Any child under the age of 5 years has died during the 5 years leading up to the survey.	1/9
Effective Access to Health Services	Any household member who has been seriously ill during the 4 weeks leading up to the survey did not have access to health services due to cost or remoteness.	1/9
Health Insurance Coverage	Any eligible household member is not covered by any health insurance scheme.	1/9
Education		
School Attendance	Any child aged 6 to 14 years old is not currently enrolled in school.	1/6
Years of schooling	No household member has completed 6 years of schooling.	1/6
Living Conditions		
Electricity	The household has no electricity.	1/18
Water	The household does not have access to improved drinking water or improved drinking water is at least a 30-minutes' walk from home, round trip.	1/18
Sanitation	The household does not have improved sanitation facilities (Water closet), or improved sanitation facilities are shared with other households.	1/18
Housing	At least one of the household's building materials for its roof, walls, or floor is inadequate.	1/18
Cooking Fuel	The household cooks with wood or charcoal.	1/18
Assets	The household does not own strictly more than one of these assets: motorcycle, refrigerator, TV, phone, computer; and does not own a car, a truck, or a tractor.	1/18

Note: Normative choice by author guided by national development goals, international SDGs, and data availability.

When excluding health insurance coverage, for which the headcount ratio in 2013 is still remarkably high but descends in later waves, only 56 percent or less of individuals who could be deprived in both indicators are indeed suffering from both deprivations, which is not a high overlap and shows the specificity of each indicator in designating poverty.

Overall, we find that most of the indicators of deprivation are not strongly associated with one another, and their inclusion paints a more complete picture of poverty in its multiple dimensions.

Fig. 2. Deprivation Raw Headcounts Ratios, by Year, Percent



Note: Multidimensional Poverty refers to a k cut-off of 33 percent, Raw Headcount Ratio is the proportion of deprived population for a certain deprivation.

(iii) *Setting a Multidimensional Poverty Cut-off*

To set the most adequate multidimensional poverty cut-off, we start by computing headcounts for both types of poverty, using different lines. As we will proceed to compare both measures using cross-headcount tabulations, it is important to select cut-offs leading to similar headcounts of poverty.

Looking at Table 4, we find that using the official monetary poverty line shows similar poverty headcounts with extreme multidimensional poverty, which confirms that is set too low while these headcounts are similar, they are also extremely low and hence do not give us statistically significant results when dealing with subgroup populations.

On the other hand, we find that the official monetary vulnerability is more in line with the traditional k cut-off of 33 percent for multidimensional poverty, with headcounts mostly matching except for 2019. This paper will thus use this pair of cut-offs for all further analysis.

Table 4

Poverty Rates at Different Cut-offs by Measure of Poverty and Year, Percent

	Monetary Poverty				Multidimensional Poverty				
Cutoff	2013	2015	2017	2019	2013	2015	2017	2019	k cutoff
Poverty	3.12	2.7	1.35	1.02	3.14	1.81	1.15	0.53	50
Vulnerability	14.89	13.46	10.15	8.17	14.89	10.45	9.34	4.71	33
	33.96		27.67		26		14.98		20

Note: Poverty and Vulnerability refer to each year's actualised poverty and vulnerability lines in Morocco. Author's Calculation based on ONDH Panel Data.

4. RESULTS

(1) Static Subgroup Analysis

As we can see in Table 4, Monetary and Multidimensional Poverty, when considered at adequate cut-offs, presents similar headcounts, and downward evolution. However, the low rates of "Both poor" in Table 5 is the first indication of the mismatch in identifying the poor. This section will thus delve into subgroup comparative analysis, using cross-headcount tabulations, quintile analysis, and socio-demographic determinants analysis.

(a) *Cross-headcount Tabulations*

Cross-headcount tabulations refer to the conditional probability of being poor in one measure given a certain poverty status for the other measure. Using these tabulations, we extract exclusion errors defined as the proportion of multidimensional poor that are not monetary poor and inclusion errors referring to the proportion of Monetary poor that are not multidimensional poor (Mitra, 2014). As we can see in Table 5, inclusion and exclusion errors are extremely high: in 2019, more than 75 percent of multidimensional poor would not have been identified as monetary poor, while 77 percent of monetary poor would not be considered poor in the other measure. These important mismatches are higher than the 50 to 60 percent error found by Perry (2002) in a review of OECD countries' poverty headcounts, and also higher than what we gathered from empirical literature in most developing countries except China (see Azami, 2021).

In addition, just like Mitra (2014), we find that these errors tend to go up with each passing wave, meaning that a reduction in overall poverty also means a higher risk of misidentification of the poor.

Table 5

Poverty Headcounts, Inclusion and Exclusion Errors by Wave, Percent

	2013	2015	2017	2019
Monetary Poor	14.89	13.46	10.15	8.17
Multidimensional Poor	14.89	10.45	9.34	4.71
Both Poor	5.38	3.26	2.33	1.33
Inclusion Error	63.85	75.8	77.02	83.72
Exclusion Error	63.85	68.81	75.04	71.73

Note: Monetary Poor refers to the Official Vulnerability line, Multidimensional Poor is considered with a k-cutoff of 33 percent, Inclusion Error refers to the proportion of Monetary poor that are not Multidimensional Poor, and Exclusion Error refers to the proportion of Multidimensional Poor that are not Monetary Poor, Author's calculation based on ONDH data.

(b) *Quintile Analysis*

Another way to compare both measures of poverty is to probe for multidimensional poverty amongst consumption quintiles. Table 6 presents multidimensional poverty headcounts by consumption quintiles for all waves. As the consumption poverty line (here the official vulnerability line) is set below the cut-off between the first and second quintile, individuals from the second quintile upwards are not monetary poor. Still, we observe relatively high multidimensional poverty headcounts for the second consumption quintile population: it reached 18.39 percent in 2013 higher than the overall multidimensional poverty headcount of 14.89 percent. We observe similar patterns amongst the third and fourth quintiles, and even the richest consumption quintile presents with a noticeable multidimensional poverty headcount, at 4.08 percent in 2013 (see Table 6). This is in line with Sumarto and De Silva (2014) who found a 4 percent multidimensional poverty occurrence for the richest consumption quintile in Indonesia, but lower than the 30 percent figure found by Levine et al. (2012) in Uganda. We note however that these occurrences tend to subside with the decline of overall poverty: only 0.63 percent of the monetary richest were multidimensional poor in 2019.

Table 6

Multidimensional Poverty Headcounts for Consumption Quintiles by Waves, Percent

Consumption Quintile	2013	2015	2017	2019
First *(Poorest)*	34.3	24.23	4.36	12.56
Second	18.39	12.14	2.46	5.05
Third	9.84	8.68	1.22	3.42
Fourth	7.61	5.1	0.76	1.93
Fifth *(Richest)*	4.08	3.4	0.54	0.63

Note: Consumption Quintile refers to survey-weighted Annual Consumption per capita, Multidimensional poverty is calculated with a k-cutoff of 33 percent, the Author's calculation based on ONDH data.

(c) *Socio-Demographic Analysis*

Furthermore, we probe for differences in poverty determinants for both measures, by computing logistic regression models with a set of socio-demographic independents variables in 2017 (see Table 7). Similar to Salecker, et al. (2020), we include the log of household consumption per capita as an additional independent variable in Model 3, in order to explore the marginal effect of consumption on multidimensional poverty and on the model fit as a whole. All models use stratified sampling weights to account for sampling design and standard errors account for clustering. They correctly classify more than 83.91 percent of observations which represents an excellent predictive accuracy (Hosmer, et al. 2013), and have an area under the ROC curve superior to 0.811, which indicates an excellent model fit (Hosmer, et al. 2013).

(i) Individual Variables

We find that the marginal effect of being a female compared to being a male on monetary and multidimensional poverty is statistically significant in Models 1 and 2. On the other hand, the age of the individual was found to have a statistically significant effect on monetary poverty only. However, it is a negligible effect in absolute terms.

(ii) Household Variables

Having an unemployed household head only has a statistically significant effect on multidimensional poverty in model 2, increasing the risk of poverty by 2.4 percent controlling for other variables.

Table 7

Estimated Marginal Effects Logistic Regression Models, 2017[2]

	Dependent Variable		
	Monetary Poverty	Multidimensional Poverty	
Model	(1)	(2)	(3)
Independent Variables			
Female Individual	0.010**	0.071**	0.005
	(0.002)	(0.002)	(0.003)
Age of Individual	–0.0003***	–0.0005	0.000
	(0.000)	(0.00009)	(0.000)
Age of Household Head	–0.0015**	–0.0009*	–0.001
	(0.00008)	(0.0004)	(0.000)
Unmarried Household Head	–0.048*	0.028	0.020
	(0.023)	(0.017)	(0.016)
Unemployed Household Head	0.017	0.024*	0.018
	(0.016)	(0.012)	(0.012)
Household Size	0.0272***	–0.0023	0.007**
	(0.0029)	(0.0025)	(0.003)
Habitation is Owned	–0.0342***	–0.0263	–0.014
	(0.0029)	(0.013)	(0.013)
Rural Location	0.1497***	0.2273***	0.174***
	(0.0174)	(0.0179)	(0.017)
Distance	0.0041**	0.0077**	0.007***
to All–weather Roads (km)	(0.0013)	(0.0015)	(0.001)
Log Household Consumption per Capita (MAD)	–	–	0.127***
			(0.013)
Observations	35152	35152	35152
Correctly Classified (%)	83.91	84.03	84.78
Area under ROC curve	0.815	0.811	0.833

Note: Models are survey-weighted and standard errors (in parentheses) account for clustering. Monetary Poverty refers to the National Vulnerability threshold, Multidimensional Poverty is measured with a 33 percent k-cutoff. Significance levels: ***=0.001, **=0.01, *==0.05.

On the other hand, having an unmarried household head is associated with statistically significant marginal effects for monetary poverty only, lowering the risk of poverty by 4.8 percent and holding all other variables constant. This might be due to not using equivalence scales in monetary poverty, favouring smaller households, which are more likely to have an unmarried household head.

Indeed, we find that for each additional household member, the risk of monetary poverty increases by 2.72 percent while controlling for other variables. However, household size does not have a statistically significant marginal effect on multidimensional poverty in Model 2, and only has a negligible marginal effect in Model 3, when including consumption as a dependent variable. Tabulating poverty headcounts with household size (see Figure 1) we find similar findings: the bigger the household, the higher the risk for monetary poverty. In addition, and similar to Tran et al. (2015), we find that multidimensional poverty presents with a convex relationship to household size, with poverty headcount higher for small and big households while 4-member households were the least poor.

[2] We only use a single year model here because some important independent variables are missing for previous years (owned habitation/distance to all-weather road).

Finally, we find that owning habitation presents a statistically significant effect on monetary poverty only, lowering the risk of poverty by 3.42 percent while controlling for other variables.

(iii) Location Variables

Compared to living in urban areas, the estimated effect of living in a rural area is statistically significant and positive for both monetary and multidimensional poverty. However, similar to Salecker, et al. (2020), we find that the effect is stronger for multidimensional poverty (22.73 percent) than for monetary poverty (14.97 percent) while holding other variables constant.

Finally, and given that the EPM 2017 cross-section is representative at the regional level, we compare monetary and multidimensional poverty rankings to find important dissimilarities (see Table 8). The two measures, present with different orderings: Draa-Tafilalet is considered the poorest in monetary terms but ranks mid-level (7/12) in multidimensional terms and Beni-Mellal Khenifra is the poorest in multidimensional terms but ranks mid-level in monetary terms (6/12).

(iv) Consumption Levels

The inclusion of the log of consumption per capita as an independent variable only slightly increases the accuracy and fit of the model. This shows that consumption doesn't play a key role in segregating multidimensional poor and non-poor. In addition, we find that while the marginal effect of consumption per capita on multidimensional poverty is significant at the 0.013 percent level, it is not strong in absolute terms: doubling an individual's consumption only decreases its chance of falling into multidimensional poverty by 12.7 percent holding all other variables constant.

Fig. 1. Poverty Headcount by Household Size in 2017, Percent

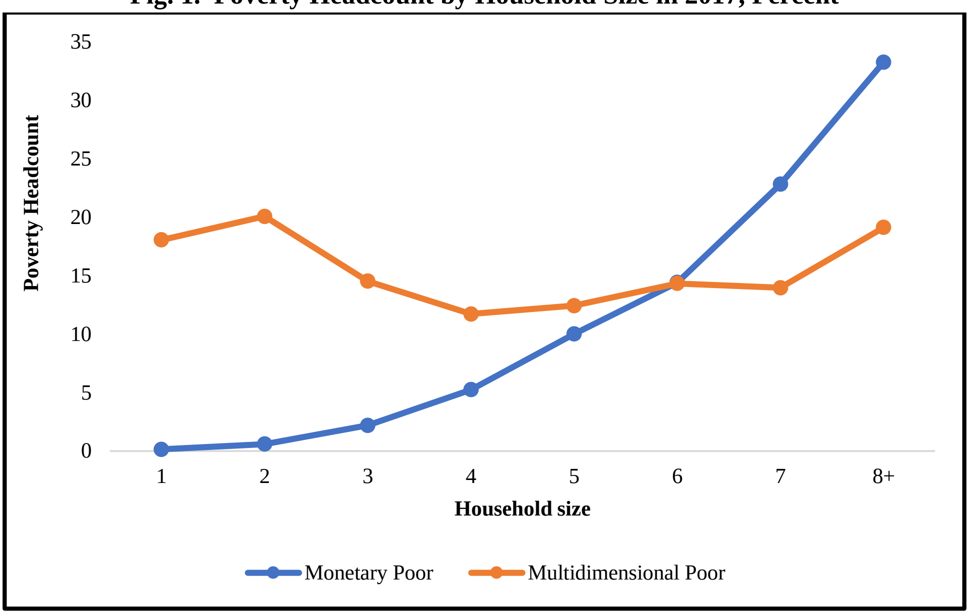


Table 8

Poverty Headcounts and Ranks by Region, 2017[3]

	Consumption Poverty		Multidimensional Poverty	
Region	Headcount (%)	Rank	Headcount (%)	Rank
Dakhla-Oued Ed-Dahab	0	1	1.29	2
Laâyoune-Sakia El Hamra	1.99	2	0.31	1
Guelmim-Oued Noun	4	3	3.29	3
Casablanca-Settat	5.59	4	7.37	6
Tanger-Tétouan-Al Hoceima	6.94	5	9.36	8
Béni Mellal-Khénifra	8.19	6	16.4	12
Rabat-Salé-Kénitra	9.24	7	7.04	5
Souss-Massa	10.56	8	10.78	10
Fès-Meknès	12.2	9	10.16	9
L'Oriental	12.6	10	5.81	4
Marrakech-Safi	16.06	11	12.99	11
Drâa-Tafilalet	23.47	12	7.85	7

Note: Consumption Poverty refers to National Vulnerability line, Multidimensional Poverty is calculated with a 33 percent k-cutoff.

In summary, we find that the measures differ significantly across sub-groups of the population and present an important level of mismatch in a static setting. This finding is in line with the argument that consumption is a poor proxy of welfare (Thorbecke, 2007). Will this mismatch resolve when taking a dynamic lens?

(2) Dynamic Comparison of Monetary and Multidimensional Poverty

Like Tran, et al. (2015) and Suppa (2016), we now use a panel of individuals present through all waves to probe for differences in mobility and poverty transitions for both measures. We then delve further into the drivers of multidimensional poverty, to find the origin of the mismatch.

(a) *Differences in Mobility*

We use a joint probability matrix over the first and last wave (2013 and 2019) to compare the mobility of monetary and multidimensional poverty. Table 9's left panel shows monetary poverty transitions using the official vulnerability line, while the right panel presents multidimensional poverty transitions. The values in the diagonal show the share of individuals for which poverty status has not changed over the period. We find that 16 percent of panel individuals have switched monetary status while 14.7 percent have switched to multidimensional poverty status.

Another way to compare mobility for both measures is by computing headcounts by number of poverty episodes (Table 10). We find similar headcounts for the chronic poor (4 episodes of poverty), with 0.9 percent chronic monetary poor and 1 percent chronic monetary poor. However, we find a larger cohort of "never poor" with multidimensional poverty (72.5 percent) than with monetary poverty (66.4 percent)

[3] The sample data is not representative on the regional level for previous years.

Overall, we find quite minor differences in mobility between monetary and multidimensional which is surprising given the assumed hypothesis that "stock" indicators such as adult literacy and health access carry more inertia than consumption or income (Clark & Hulme, 2005). In line with Tran, et al. (2015), we find that multidimensional measures are also sensitive to change over time and thus might reflect changes in the economy as well as government policy responses. In the case of Morocco, the rollout of health insurance coverage starting in 2012 seems to have contributed to the downward evolution of multidimensional poverty in the second wave, as we will see in the last section.

Table 9

Join Probabilities between Monetary and Multidimensional Poverty, Percent

	MN 2019		MD 2019		
MN 2013	Poor	Non-Poor	Poor	Non-Poor	MD 2013
Poor	3.7	11.0	2.3	12.9	Poor
Non-Poor	5.0	80.3	1.8	82.9	Non-Poor

Note: MN refers to the official monetary vulnerability line, and MD refers to multidimensional poverty with a k cut-off of 33 percent.

Table 10

Headcounts by Episodes of Poverty, Percent

Episodes of Poverty	MN Poverty	MD Poverty
0 *(Never Poor)*	66.4	72.5
1	18.3	15.1
2	9.9	7.9
3	4.3	3.6
4 *(Always Poor)*	0.9	1.0

Note: MN refers to the official monetary vulnerability line, MD refers to multidimensional poverty with a k cut-off of 33 percent, and an episode of poverty corresponds to being identified as poor at one time period.

(b) *Dynamic Poverty Cross-tabulations*

While we found in the previous section that both measures display similar mobility, it would be interesting to probe the mismatch at the dynamic level and see if monetary and multidimensional poverty transitions concern the same subgroups of individuals in our panel. Table 11 shows a tabulation of multidimensional poverty given a certain monetary poverty status over the four periods. Transient poverty is defined as experiencing 1 or 2 episodes of poverty while chronic poverty definition is enlarged to include those who experience 3 episodes of poverty as well as the always poor. The level of mismatch in poverty status is important, especially for the chronic poor: only 22.7 percent of chronic monetary poor are also chronic multidimensional poor, which represents a 77.3 percent exclusion error. The "Never poor" population presents with a higher level of overlap with 82.3 of Monetary "Never poor" also multidimensional "Never poor".

Table 11

Cross-tabulation of Monetary and Multidimensional Poverty Status over time, 2013-2019, Percent

		MD Poverty		
MN Poverty	Population	Never	Transient	Chronic
Never	66.4	82.3	15.6	2.1
Transient	28.2	56.7	36.2	7.2
Chronic	5.2	32.6	44.7	22.7

Note: MN refers to the official monetary vulnerability line, MD refers to multidimensional poverty with a k cut-off of 33 percent, never refers to having encountered no poverty episode during the period, Transient refers to having encountered 1 or 2 poverty episodes, and Chronic to have encountered 3 or 4 poverty episodes.

We then probe this mismatch further by tabulating multidimensional poverty transitions given a certain monetary poverty trajectory. Table 12's upper matrix presents these conditional poverty trajectories for the 2013-2015 period while the lower matrix presents their equivalent for the 2015-2017 period. The first row of the upper matrix shows us that 75.9 percent of the total panel individuals stayed non-poor between 2013 and 2015, amongst which 83.9 percent stayed non-poor by the multidimensional measure, and 7.1 percent got out of multidimensional poverty. However, 4.7 percent of these non-poor in monetary terms fell into multidimensional poverty and 4.3 percent stayed in it during the same time period. Looking at the subgroup that stayed poor during the period, we find a higher level of mismatch multidimensional measure trajectories: only 27.5 percent stayed poor while 17.1 percent escaped poverty and 41.3 percent were non-poor, to begin with. The mismatch in trajectories is more important for individuals rising from or falling into monetary poverty during the period: only 18.9 percent of those who rose from monetary poverty also rose from multidimensional poverty while 8.9 percent fell into it at the same period.

Analysis of the lower matrix gives us the same insight: monetary and multidimensional transitions seem to be strongly correlation for the non-poor, moderately correlated for the chronically poor, and weakly or non-correlated for those whose status changes within a period. This suggests that the transitions in poverty status in one measure are not accompanied by simultaneous transitions in the other measure: in fact, the opposite transition is more likely to happen in the case of those falling into monetary poverty. This is in line with Seff & Jolliffe (2016) who in Ethiopia found that 41 percent of those multidimensional measures worsened saw their consumption poverty improve while 53 percent of individuals whose multidimensional measures improved, saw their consumption poverty worsen.

Hence, the seemingly slight differences in mobility that we previously found, are not a sign of a larger overlap of the two measures when considered in a dynamic setting as most of the individuals making the transitions in one measure are different from the one switching status in the other measure. We find similar mismatches between the two measures when looking at poor populations in a dynamic and static setting. Indeed, Table 11 gives us an inclusion error of 64.7 percent for transient poverty and 77.3 percent for chronic poverty, which is within the 63-83 percent range of errors found previously for every cross-section (see Table 5).

This finding is not in line with the theoretical argument made by Hulme, et al. (2001) that multidimensional and monetary poverty should reinforce one another and also not in line with Whelan, et al. (2004) which found a higher overlap between the two measures when analysing them in a dynamic setting. It is in line with the capability approach argument that monetary measures may not be a good proxy for public goods, as we shall see in the next section.

Table 12

Cross-tabulation of Monetary and Multidimensional Poverty Trajectories, Percent

Monetary Poverty Trajectory	Population Share	Multidimensional Poverty Trajectory			
		Non-Poor	Rising	Falling	Staying Poor
2013-2015					
Non-Poor	75.9	83.9	7.1	4.7	4.3
Rising	10.0	59.3	18.9	8.9	12.9
Falling	8.9	63.8	13.6	8.9	13.7
Staying Poor	6.2	41.3	17.1	14.1	27.5
2015-2017					
Non-Poor	76.1	86.3	6.2	4.4	3.1
Rising	10.5	68.1	14.8	11.7	5.4
Falling	8.9	65.8	15.5	8.5	10.3
Staying Poor	4.5	56.2	12.0	10.6	21.2

Note: Monetary Poverty refers to the official monetary vulnerability line, and Multidimensional Poverty refers to the k cut-off of 33 percent.

(c) *Decomposition of Multidimensional Poverty Transitions*

While we found that both measures present an important mismatch at the dynamic level, it would be interesting to examine which indicators in particular are responsible for this disagreement. Figure 2 shows deprivation headcount ratios for the whole panel population encompassing the 4 waves: insurance coverage has the highest deprivation ratio by far, followed by adult literacy, housing, effective access to health services, child schooling, and water. On the other hand, Child mortality, cooking, assets, and electricity display low rates of deprivation throughout. Most indicators saw improvements overall, especially the education and health indicators, with the health insurance coverage ratio going from 73.8 percent in 2013 to 40.6 percent in 2019: this explains the overall downward tendency of the multidimensional poverty headcount as education and health indicators account for two-thirds of the measure. However, not all these indicators saw linear downward progress, with slight increases in adult illiteracy in 2017 and setbacks in effective access to health and electricity in 2015.

Looking at the subgroup of the panel that made a multidimensional poverty transition in the two first periods, we computed the change in headcount ratios for each of the 11 indicators (see Table 13). We find that the education indicators are the key drivers for those who entered poverty in the first period, with more than 36.9 percent of this sub-population also becoming deprived of child schooling and 31.5 percent becoming deprived of adult literacy. These are followed by the effective access to health indicator, with more than 28 percent of this subgroup also becoming deprived in this indicator. For those escaping poverty, we find that adult literacy and health insurance are the two most important drivers, with 35 percent of the subgroup also exiting literacy deprivation and 32.2 percent also exiting insurance deprivation.

These important dynamics in education and health indicators could be unrelated to the purely monetary conditions of an individual and play a role in the important mismatch in monetary and multidimensional poverty transitions.

Figure 2. Deprivation Raw Headcounts Ratios, by year, Percent

Table 13

Changes in Raw Headcounts Ratios for Multidimensional Poverty Transitions by Indicator and Time-period

	Change in Raw Headcount Ratio					
	2013-2015		2015-2017		2017-2019	
Indicator	Entry	Exit	Entry	Exit	Entry	Exit
Schooling	–36.9	+24.8	–36.8	+30.9	–32.4	+29.7
Literacy	–31.5	+35.0	–43.9	+33.2	–41.2	+31.7
Child Mortality	–3.3	+8.2	–1.7	+4.2	–2.1	+3.3
Access to Health	–28.7	+19.2	–32.2	+23.9	–36.4	+27.8
Health Insurance	–6.9	+32.2	–15.2	+37.6	–14.7	+34.5
Electricity	–4.0	+6.1	+2.3	+9.1	+1.2	+7.6
Water	–10.4	+19.4	–6.3	+14.7	–3.4	+21.3
Sanitation	–20.4	+20.1	–9.3	+20.4	–5.7	+19.5
Housing	–13.0	+20.3	–17.6	+23.1	–15.7	+22.4
Cooking	–3.9	+4.1	+2.7	+3.5	+3.5	+4.1
Assets	–6.6	+3.4	–2.0	+10.8	–5.7	+11.2
Population Share	5.8	2.2	5.7	8.2	2.3	4.3

Note: Multidimensional Poverty refers to a k cut-off of 33 percent, Raw Headcount Ratio is the proportion of the deprived population for a certain deprivation, Entry refers to falling into poverty, and Exit refers to leaving poverty.

5. CONCLUSION

Using the first panel data ever produced in Morocco for the period from 2013 to 2019, we applied the Alkire Foster methodology to probe for differences between monetary and multidimensional poverty. For that purpose, we started with a static analysis, investigating the mismatch between both measures in the same cross-section and for different subgroups. We then moved to a dynamic setting to compare poverty transitions in a restricted panel of individuals who were present in all four waves.

We found an important mismatch between monetary and multidimensional measures on all levels. On a static level, while displaying similar headcounts, the two measures identified different populations as poor, with high levels of exclusion error (the percentage of multidimensional poor who are not monetary poor) and inclusion error (the percentage of monetary poor who are not multidimensional poor) for all four cross-sections. Delving deeper into subgroup analysis, we find that multidimensional poverty is present even amongst the richest monetary quintile and that doubling consumption figures would only decrease the risk of multidimensional poverty by 12.7 percent, which implies that an increase in consumption does not necessarily lead to an improvement in non-monetary indicators. In addition, the two measures present with substantially different poverty determinants, and thus might refer to different "poverty phenomena"

(Thorbecke, 2007): rural dwellers are more prone to multidimensional poverty, and bigger households are more prone to monetary poverty, while household size has a convex relationship with multidimensional poverty.

Taking a dynamic lens, we find that the level of mismatch between the two measures does not improve, and that multidimensional poverty shows surprisingly high dynamics. Despite similar levels of mobility, transitions in poverty status in one measure are not accompanied by simultaneous transitions in the other measure. This is in line with previous empirical studies in Ethiopia (Seff & Jollife, 2016) and Vietnam (Tran, et al. 2015) but not in line with the theoretical argument that both types of poverty tend to reinforce each other (Hulme, et al. 2001).

We also found that the main drivers behind transitions in multidimensional poverty were the education and health indicators, particularly adult illiteracy for falling into poverty, and insurance coverage for escaping poverty. These indicators are intimately linked to government interventions in Morocco, with subsidised insurance coverage for the poor and adult literacy programmes as one of the key development policies in the country. They can be considered non-market goods for which consumption or income are weak proxies, in line with the capability approach.

Policy-wise, our study suggests that the currently used official poverty and vulnerability lines may exclude a sizeable portion of the multidimensional poor. This might prove problematic as the Moroccan government uses proxy test targeting based on these monetary lines precisely to target people deprived of health access or insurance for example (Cottin, 2019): we thus recommend the concomitant use of non-monetary measures to allow for better targeting. We also suggest raising the official monetary line to the level of the current vulnerability line, to better reflect Morocco's current level of development.

It is worth mentioning that our study only spans 6 years in total (2013-2019) and that further studies on the dynamic mismatch between the two measures of poverty might use a longer period, with new waves of the EPM, for example. In addition, we were constrained by data for the specification of our multidimensional measure: it would have been interesting to explore the mismatch dynamics with nutrition (anthropometric measurements) as a health indicator, similar to the GMPI.

ANNEX

Table A1

Cramer V's between Multidimensional Deprivation Indicators, 2013

	School	Literacy	Mortality	Health	Insurance	Electricity	Water	Sanitation	Housing	Cooking	Assets
School	1.00										
Literacy	0.13	1.00									
Mortality	0.01	0.03	1.00								
Health	0.00	0.04	0.03	1.00							
Insurance	0.05	0.06	0.01	0.04	1.00						
Electricity	0.05	0.12	0.00	0.09	0.00	1.00					
Water	0.11	0.16	0.05	0.01	0.08	0.11	1.00				
Sanitation	0.04	0.12	0.06	0.07	0.00	0.14	0.15	1.00			
Housing	0.10	0.20	0.04	0.10	0.09	0.16	0.22	0.11	1.00		
Cooking	0.06	0.09	0.05	0.04	0.02	0.12	0.07	0.09	0.19	1.00	
Assets	0.05	0.15	0.03	0.10	0.00	0.52	0.10	0.14	0.18	0.11	1.00

Notes: School refers to child school attendance, Literacy refers to adult literacy, Mortality refers to Child Mortality, Health refers to effective access to health services, Insurance refers to health insurance coverage, Cooking refers to cooking fuel. Cramer's V values are significant at the 99 percent confidence level.

Table A2

Redundancy Table for Multidimensional Deprivation Indicators, 2013

	School	Literacy	Mortality	Health	Insurance	Electricity	Water	Sanitation	Housing	Cooking
Raw Headcount Ratio	6.0	24.4	1.1	11.7	72.6	2.6	11.2	10.0	15	1.8
Literacy	0.47									
Mortality	0.13	0.38								
Health	0.11	0.28	0.15							
Insurance	0.80	0.79	0.75	0.79						
Electricity	0.14	0.55	0.01	0.23	0.75					
Water	0.25	0.42	0.28	0.12	0.83	0.32				
Sanitation	0.18	0.42	0.25	0.20	0.75	0.40	0.27			
Housing	0.28	0.44	0.25	0.25	0.82	0.50	0.38	0.31		
Cooking	0.16	0.54	0.07	0.27	0.80	0.19	0.23	0.39	0.69	
Assets	0.12	0.55	0.05	0.26	0.72	0.54	0.26	0.36	0.5	0.22

Notes: School refers to child school attendance, Literacy refers to adult literacy, Mortality refers to Child Mortality, Health refers to effective access to health services, Insurance refers to health insurance coverage, Cooking refers to cooking fuel.

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