DISCUSSION PAPER SERIES

Measuring Monetary Poverty in the Middle East and North Africa (MENA) Region: Data Gaps and Different Options to Address Them

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ABSTRACT

Measuring Monetary Poverty in the Middle East and North Africa (MENA) Region: Data Gaps and Different Options to Address Them*

This paper identifies gaps in availability, access, and quality of household budget surveys in the Middle East and North Africa region used to measure monetary poverty and evaluates ways to fill these information gaps. Despite improving public access to household budget surveys, the availability and timeliness of welfare data in the Middle East and North Africa region is poor compared to the rest of the world. Closing the data gap requires collection of more HBS data in more countries and improving access to data where it exists. However, when collection of consumption data is not possible, a variety of other second-best strategies can be employed. Using imputation methods can help to measure monetary poverty. Constructing non-monetary poverty and asset indexes from less robust surveys, using non-traditional surveys such as phone surveys, and "big data"—administrative records, social networks and communications data, and geospatial data—can help substitute for, or complement data from existing traditional survey data.

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1. Introduction

Household budget surveys (HBSs) are commonly used to collect information about household expenditure, consumption, income, and other aspects of social development. National governments and international organizations use these multipurpose surveys to design public policies to improve socio-economic well-being (Deaton, 2018) and to monitor progress in achieving many Sustainable Development Goals (Ferreira et al., 2016). Household budget surveys are also exclusively used by the World Bank to track the goals of ending extreme poverty and promoting shared prosperity.

Availability and access to household budget surveys along with regular reporting of monetary poverty are important components of the overall statistical capacity of a country. The Middle East and North Africa region (MENA) stands out for its low statistical capacity, lagging behind other regions in 2019 according to the statistical capacity indicator developed by the World Bank. According to Arezki et al. (2020), loss of data transparency and capacity has cost the MENA region about 7-14 percent in GDP per capita losses since 2005.

Although availability and access to household budget surveys has been improving in selected countries in the MENA region during the last decade, many challenges and data gaps remain (Serajuddin et al., 2015). For example, household budget surveys (HBSs) are not collected regularly in many countries and are often not comparable across years, limiting the ability to monitor development indicators. As it stands today, more than half of the countries in the region conducted two or fewer surveys between 2004 and 2018. This results in about 46 percent of MENA's population living in data deprived countries.

Partially this is related to violent conflicts in some countries, including Iraq, Libya, the Syrian Arab Republic, and the Republic of Yemen. Conflicts prevent any traditional data collection due to security issues. Moreover, conflicts may affect poverty quickly and make existing data outdated and unable to capture the changes. There are also many countries in the MENA region which do not collect HBSs regularly or do not share the microdata with the public. All these issues restrict the ability of governments, academics, and international organizations to monitor welfare in the region and to have informed policy discussions (Demombynes and Sandefur, 2014; Serajuddin et al., 2015).

To our knowledge, there are several papers looking into the issue of availability of household budget surveys. Demombynes and Sandefur (2014) explored the supply of household surveys during 1980-2010 and estimated the costs of filling remaining gaps. Serajuddin et al. (2015) analyzed data deprivations globally, focusing on HBSs and poverty estimates during 1990-2011. Both papers provided very useful overviews of HBS availability, but neither conducted a detailed review in the MENA region nor discussed options to fill the gap using different methods to measure poverty and well-being.

This paper fills the gap by focusing only on the MENA region[2] and explores in detail the availability, access and quality of the HBSs collected during last 15 years (2004-2018). The paper gives an overview of non-traditional methods of data collection in cases when collecting an HBS is not possible. It also offers a comprehensive list of potential options to estimate either monetary poverty or other indicators of well-being in the region. Survey-to-survey imputation, multidimensional poverty indexes (MPIs), phone

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[2] The MENA region includes here only 13 developing countries (Algeria, Djibouti, Egypt, the Islamic Republic of Iran, Iraq, Jordan, Lebanon, Libya, Morocco, the Syrian Arab Republic, Tunisia, West Bank and Gaza and Yemen) and excludes rich Gulf countries.

surveys, public opinion surveys and different "big data" approaches are some of the alternatives discussed.

The paper is organized as follows. Section 2 discusses the importance of having regularly conducted HBSs[3] to measure monetary poverty. Section 3 describes the evolution of the statistical capacity of MENA. Section 4 summarizes the availability of HBSs in the region and compares data availability to that in other regions. Section 5 presents potential ways to address gaps in data availability and innovative data approaches to supplement existing estimates of monetary poverty. And Section 6 concludes.

2. Importance of household budget surveys in measuring and understanding monetary poverty

"Household budget surveys" (HBSs) is a generic term covering a broad category of surveys that might also be referred to as "family expenditure surveys" or "income and expenditure surveys", among others. The common goal of these surveys is to collect information about household "budgets" reflected in expenditure, consumption or/and income. Many surveys add other modules to the core consumption/expenditure section, to collect information on education, labor market, nutrition, and housing conditions. The most common practice is to use consumption, expenditure, and income to derive a money-metric measure to calculate poverty rates (Dang et al. 2019).[4] National governments and international organizations use HBSs to inform poverty monitoring systems which track progress towards achieving regional/global poverty targets and which help formulate operational policies.

Having comparable and up-to-date household budget surveys is crucial for monitoring global and regional poverty trends. To measure extreme poverty at the international poverty line (USD1.90 2011 purchasing power parity (PPP) exchange rates), the World Bank uses either current consumption/income distributions from the most recent surveys or updates old distributions using GDP per capita or private consumption growth rates.[5] In addition, the World Bank uses consumer prices indexes (CPI) and PPP exchange rates to account for variations in prices across countries and to convert distributions from local currency units to a comparable international currency.

Lack of a recent HBS for a country leads to omission from global and regional poverty counts because outdated surveys provide outdated distributions, which, if included, would lead to inaccurate poverty estimates (this also depends on the quality of macroeconomic numbers and their underlying relationship with household well-being --see detailed explanation and empirical results illustrating the issues in the Annex). For these reasons, if surveys are two years older than the reference year selected for reporting of global poverty numbers, and outdated surveys account for more than 60 percent of regional population, regional poverty estimates are not reported.

Until recently, MENA did not report regional poverty due to the lack of recent HBSs but also because of the presence of unreliable PPP exchange rates for several MENA countries (Atamanov et al., 2018). Once

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[3] Several countries measure income poverty using labor force surveys, for example the Dominican Republic and Ecuador. However, these cases are exceptions and this practice is rare. We discuss briefly the issue of using labor force surveys to measure poverty and its applicability to the MENA region in the Annex.

[4] Leaving aside the debate about different approaches to measure household welfare, we use "consumption", "expenditure" and "income" terms interchangeably as measures of household living standards.

[5] Find a detailed explanation of issues related to monitoring of global/regional poverty in the Annex.

the issue of PPP factors was solved and a critical number of recent surveys was reached in 2017, MENA regional poverty rates were reported again. In the 2018 reference year, about 7 percent of MENA population were found to live below the extreme poverty line of USD1.90 2011 PPP per day, which more than tripled from the 2 percent reported in 2013.

Figure 1. Regional extreme poverty rates in the MENA region at $1.9 2011 PPP poverty line, 2010-2018 reference years
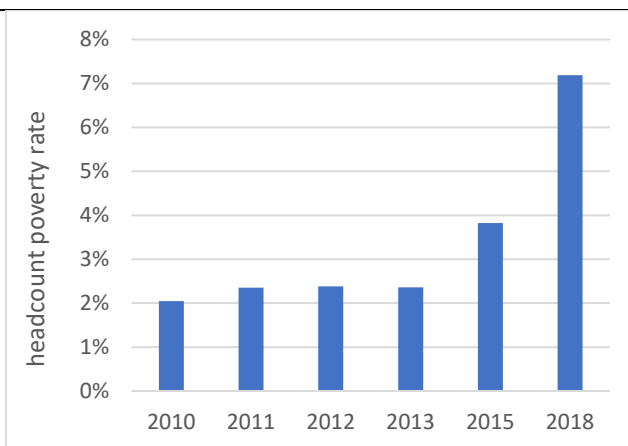

Source: PovcalNet, May 2020.

Monitoring progress on the World Bank's goal of boosting "shared prosperity"—defined as the income growth of the bottom 40 percent in any given country—is even more demanding in terms of data requirements. Measuring consumption/income growth across two points in time requires two comparable welfare aggregates constructed from two recent household surveys (Atamanov et al., 2016). Currently, only four countries in the MENA region meet these criteria and are included in the global shared prosperity database (2012-2017) (Figure 2).

As mentioned above, besides collecting detailed consumption data, HBSs collect information on aspects of human and social development. Thus, the usefulness of these surveys goes well beyond monitoring monetary poverty. Collecting household and individual characteristics along with locational attributes makes these surveys important for policy makers who want to design and understand the impact of public policies on socio-economic well-being. For example, the World Bank uses household and individual characteristics from HBSs to prepare profiles of the poor, or estimate the bottom 40 percent at country, regional, and global levels. These individual and household characteristics are harmonized to enable cross-country analyses and are used in all World Bank flagship reports on poverty, shared prosperity, and economic mobility, and in different briefs.[6]

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[6] For example, the World Bank produces regular Poverty and Shared Prosperity reports, which provide a global audience the latest and most accurate estimates on trends in global poverty and shared prosperity. The reports also provide in-depth research into policies and interventions that can make a difference for the world's poorest. The World Bank also produces bi-annual Country Poverty and Equity Briefs (PEBs), which highlight poverty, shared prosperity, and inequality trends, and provides the context of poverty and equity conditions in more than 100 countries.

Figure 2. Global shared prosperity database (circa 2012-2017)
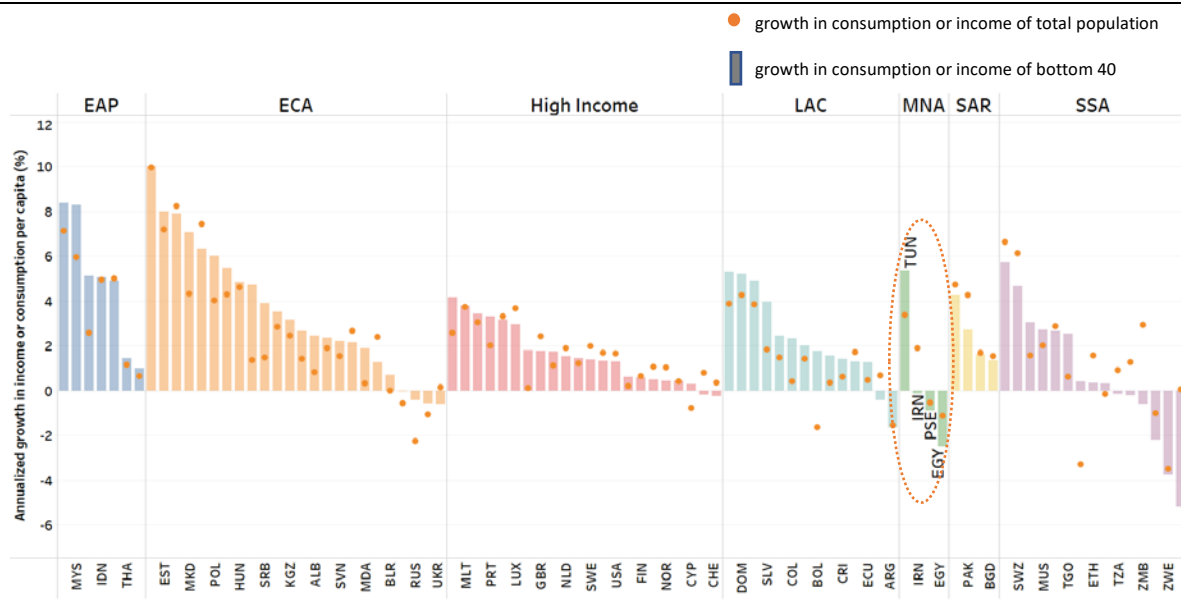
Source: World Bank Global Shared Prosperity database, May 2020.
Note: TUN stands for Tunisia, EGY stands for the Arab Republic of Egypt, Arab Republic, PSE stands for West Bank and Gaza and IRN stands for the Islamic Republic of Iran.

Additional information collected in HBSs also allows monitoring non-monetary dimensions of poverty. Many countries complement monetary poverty estimates with multidimensional poverty indexes, which give a broader perspective on non-monetary deprivations. Following Atkinson's report (World Bank, 2017), the World Bank started constructing multidimensional poverty by using HBSs to better measure non-monetary dimensions of poverty, such as education and access to infrastructure. This practice is now followed in many developing countries (see Santos, 2019 for a review).

3. Statistical capacity in the MENA region

The World Bank has developed an indicator to measure the capacity of national statistical systems.[7] The indicator uses metadata information and monitors progress in statistical capacity building over time. The indicator covers three aspects: statistical methodology; source data; and periodicity and timeliness. Statistical methodology measures a country's ability to adhere to internationally recommended standards and methods. Source data evaluate whether a country conducts data collection in accordance with internationally recommended periodicity and whether data from administrative systems are available and reliable for statistical estimation purposes. Finally, periodicity and timeliness look at the availability and periodicity of key socioeconomic indicators. This paper uses this composite indicator to assess MENA's statistical capacity, which goes beyond HBSs and refers to overall data systems in a particular country.

Figure 3. Statistical capacity indicators in different regions in 2005, 2010, 2015 and 2019

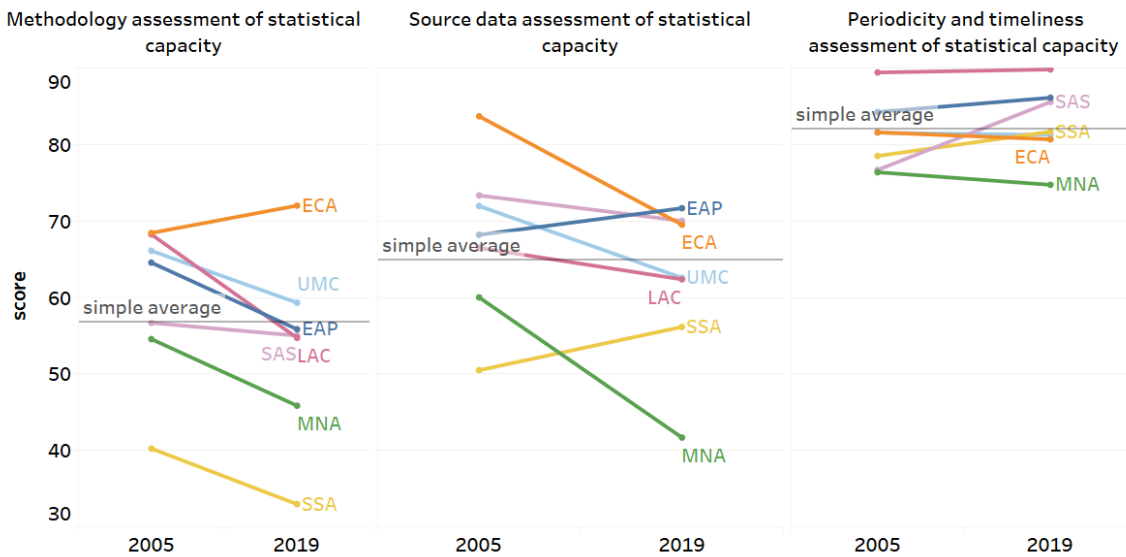
[7] http://datatopics.worldbank.org/statisticalcapacity/Home.aspx.
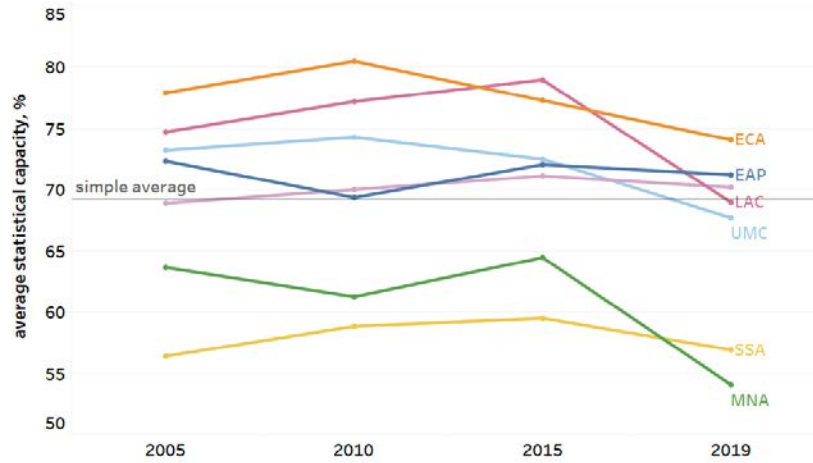
Figure 4. Three dimensions of statistical capacity indicators in different regions

The MENA region stands out for its low and falling statistical capacity. As shown in Figure 3, statistical capacity in MENA lags behind other regions except Africa and has fallen between 2015 and 2019. If we take into account the level of economic development, the gap in statistical capacity is even more striking. Regarding country level performance, conflict affected countries such as Iraq, Libya, the Syrian Arab Republic, and Yemen have the lowest statistical capacity score, and the situation worsened in the last two countries during 2015 to 2019.

The MENA region has particular problems related to availability and timeliness of statistical data and indicators. Figure 4 shows the performance of each region in each of the three statistical capacity

dimensions. MENA did worse in all of them during the considered period. MENA even had a lower score in these last two dimensions than the much poorer Africa region.

4. Household budget surveys in the MENA region

<u>Availability, timeliness, and access</u>

Regional picture

Household budget surveys (HBSs) collect detailed information about individual/household expenditure, consumption, and income, and also collect household demographic and socio-economic characteristics. This information is used to measure monetary poverty. Most HBS surveys last one full year to allow accounting for seasonal variations in consumption/income. Once primary data collection is finished, data cleaning and poverty measurement can take one year to be completed. It is advisable to conduct HBSs regularly at least once every three to five years (Serajuddin et al., 2015). Given rapid changes in the MENA region, every three-years is a more advisable benchmark, but we use the more conservative five-year gap below.

Table 1 demonstrates that the vast majority of MENA countries fall short of this benchmark. It summarizes for every region the number of countries that conducted HBSs suitable for constructing a monetary poverty metric over the past 15 years.[8] The first panel of Table 1 reports the number of countries in the region that conducted no surveys, one to two surveys, and three and more. The second panel reports the share of countries by number of surveys conducted. The third panel reports the share of the population in the respective region covered by the number of surveys conducted (as opposed to share of countries). Countries with fewer than three surveys are considered "data deprived" according to the benchmark of conducting a survey at least every five years.

Between 2004 and 2018, seven of 13 MENA countries, or more than half, conducted fewer than three surveys. This falls short of areas suitable for socio-economic comparison to MENA, such as Latin America and the Caribbean (LAC) and Europe and Central Asia (ECA). The gap between MENA, LAC, and ECA widens once the population size of each country is considered: 46 percent of MENA's population live in data deprived countries compared to 5, 1, and 0 percent in LAC, EAP and ECA, respectively.

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[8] For a comprehensive assessment of available household surveys suitable to measure poverty, we use the number of poverty statistics reported in the World Development Indicators (WDI) database for the last 15 years, 2004 to 2018 (we use both poverty headcount ratio at $1.90 a day 2011 PPP and national poverty rates including non-comparable ones). In the MENA region, we manually added information about existing household budget surveys in the Islamic Republic of Iran for each year between 2004 to 2018, Jordan for 2017 , Libya for 2007, and Egypt for 2017, countries for which we either have access to microdata or know can be, or were, used to measure monetary poverty but not included in the WDI.

Table 1. Availability of household budget surveys (measured by poverty data) by region between 2004 and 2018

Region	countries				% in total number of countries				%, population weighted			
	no data available	1-2 data points	>= 3 data points	total	no data available	1-2 data points	>= 3 data points	total	no data available	1-2 data points	>= 3 data points	total
EAP	4	11	9	24	17	46	38	100	1	1	98	100
ECA	1	0	20	21	5	0	95	100	1	0	99	100
LAC	7	3	14	24	29	13	58	100	2	5	93	100
MENA	0	7	6	13	0	54	46	100	0	46	54	100
SAS	0	2	6	8	0	25	75	100	0	2	98	100
SSA	2	27	18	47	4	57	38	100	2	58	40	100

Source: WDI (May 2020) and authors' calculation.
Note: If survey period bridges two years, the first year serves as a survey year. * average country shares in regional population during 2004-2018 are used as weights.

Figure 5 analyzes the timeliness of the most recent household survey. Outdated data are less useful if the country experiences substantial structural economic changes or shocks. The MENA region does not perform well compared to ECA and LAC on this criterion, where more than 80 percent of the most recent surveys are from 2015 to 2018. Recent data are also more current in the SAS and EAP regions. In MENA, more than 50 percent of the most recent surveys date between 2006 to 2014.

Figure 5. Distribution of the most recent household budget surveys (measured by poverty data) by data collection period
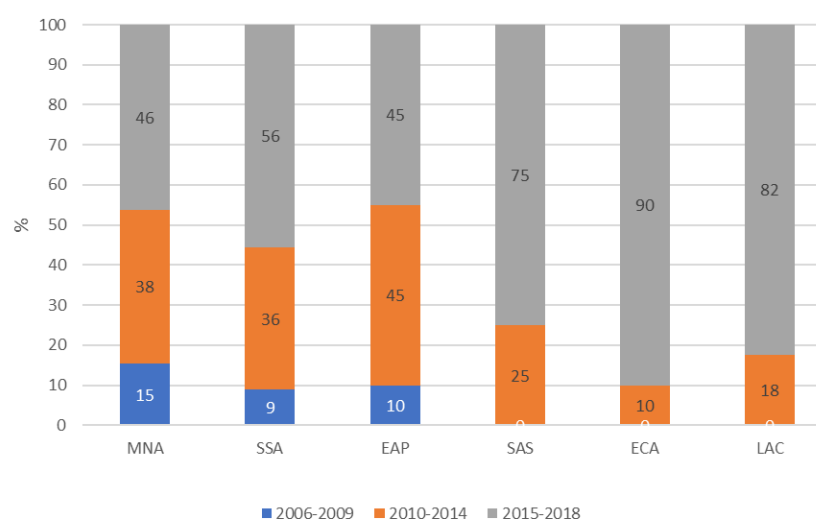
Source: WDI (October 2019) and authors' calculation Note: If survey period bridges two years, the first year serves as a survey year.

Having outdated HBSs for poverty monitoring is not always driven just by an absence of surveys; there are other potential causes. First, there can be long lags between the completion of primary data collection and the production of a poverty estimate, particularly when data collection is not computer assisted. Second, there are often long delays between the publication of a national poverty number and the sharing of the underlying data with the World Bank for use in global poverty monitoring. Sometimes data are not shared at all. Table 2 illustrates these delays for the most recent surveys in Algeria, Morocco, and Jordan.

The lag between the time when field work data collection is completed and when data can be used for global poverty monitoring may be as much as four years.

Table 2. Example of timing of different steps in poverty measurement process

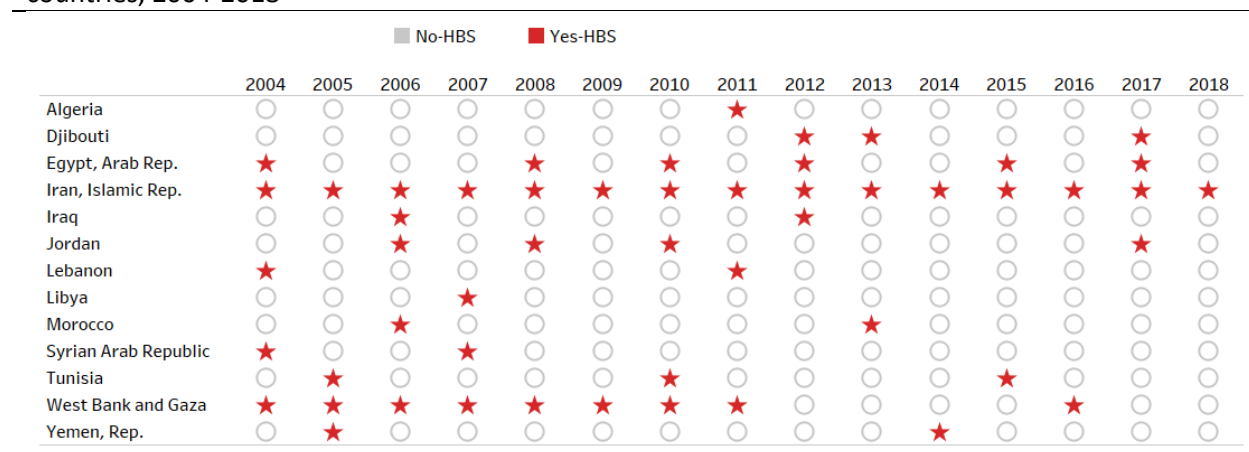|	field work completed	National poverty is announced	Data is shared with the World Bank to be used for global poverty monitoring
Morocco	2014	2015	2018
Algeria	2012	2014	2016
Jordan	2018	2018	not yet

Source: Authors' compilation from open sources.
Note: In case of Algeria, the World Bank team got access only to group data.

Country-level picture

Figure 6 shows the availability of HBSs for all developing countries in MENA. Most countries, except the Arab Republic of Egypt and the Islamic Republic of Iran, do not regularly collect HBS data. For example, Algeria and Libya conducted only one HBS, and Lebanon, Yemen, and the Syrian Arab Republic only two during last 15 years.

For many countries, HBS surveys are outdated. For example, the Syrian Arab Republic, Libya, Algeria, and Lebanon did not collect surveys after 2011. HBSs for Morocco and Yemen are also getting outdated, especially considering the drastic changes that have occurred during the armed conflict in Yemen.

Figure 6. Availability of household budget surveys to measure monetary poverty in the MENA region by countries, 2004-2018

No-HBS   Yes-HBS

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Algeria	○	○	○	○	○	○	○	★	○	○	○	○	○	○	○
Djibouti	○	○	○	○	○	○	○	○	★	★	○	○	○	★	○
Egypt, Arab Rep.	★	○	○	○	★	○	★	○	★	○	○	★	○	★	○
Iran, Islamic Rep.	★	★	★	★	★	★	★	★	★	★	★	★	★	★	★
Iraq	○	○	★	○	○	○	○	○	★	○	○	○	○	○	○
Jordan	○	○	★	○	★	○	★	○	○	○	○	○	○	★	○
Lebanon	★	○	○	○	○	○	○	★	○	○	○	○	○	○	○
Libya	○	○	○	★	○	○	○	○	○	○	○	○	○	○	○
Morocco	○	○	★	○	○	○	○	○	○	★	○	○	○	○	○
Syrian Arab Republic	★	○	○	★	○	○	○	○	○	○	○	○	○	○	○
Tunisia	○	★	○	○	○	○	★	○	○	○	○	★	○	○	○
West Bank and Gaza	★	★	★	★	★	★	★	★	○	○	○	○	★	○	○
Yemen, Rep.	○	★	○	○	○	○	○	○	○	○	★	○	○	○	○

Source: WDI (October 2019) and authors' calculation
Note: If survey period bridges two years, the first year serves as a survey year.

Public and World Bank access to HBSs in the MENA region is improving, as summarized in Table 3. Of the 13 developing countries listed in Table 1, eight share full microdata or a random sample.[9] Some countries

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[9] Access policy may be different across years. For example, Yemen's 2005 HBS is publicly available, but the 2014 survey is not. It is also not very clear why data are not shared in some countries. The most frequently used reasons for not sharing the data or sharing it with a substantial delay include legal constraints on sharing private information, risk of misuse of data by users, and necessity to finish and publish all analytical work before making the data accessible.

changed their access policy over time. For example, Tunisia initially did not share access to their 2015 survey, but later granted access as part of their engagement with the World Bank. Morocco did not share its microdata but decided in 2019 to publish online its most recent HBS. Importantly, there are instances where the World Bank provides substantial technical assistance to the National Statistics Office but where data are not shared, or where there are substantial delays before data are shared; for example, Morocco only granted access to its 2013 survey in 2018. Algeria granted access to the World Bank to group data only.

| Table 3. Status of public and WB access to household budget surveys in MENA region as of August, 2019		
Public or licensed access / partial or full	no public access	no WB engagement
Djibouti	Algeria	Libya
Egypt, Arab Rep.	Jordan	Syrian Arab Republic
Iraq	Lebanon	
Iran, Islamic Rep.		
Yemen, Rep.		
Tunisia		
West Bank and Gaza		
Morocco		
Source: Authors' compilation.		
Note: Licensed means the request to get the microdata should be cleared.		

Comparability

Regional picture

In addition to needing recent HBSs to provide current welfare metrics, comparability of these surveys across time is important to estimate trends. Poverty estimates may not be comparable for different reasons. Non-comparability arises when surveys measure either the welfare aggregate (consumption or income) differently across different years following changes in survey design or instruments or because the statistical office changes the way it constructs welfare aggregates.[10] In the absence of at least two comparable data points, it is impossible to analyze poverty or shared prosperity across time.

Figure 7 shows the distribution of countries in each region that report shared prosperity in the most recent World Bank global shared prosperity database, 2012 to 2017. Excluded are those countries that did not have two recent and comparable welfare aggregates. We distinguish between countries reporting improved shared prosperity (positive consumption or income per capita growth of the bottom 40 percent of population) and countries reporting deteriorating shared prosperity. The regions with the highest share of countries not reporting shared prosperity are Sub-Saharan Africa and MENA. Only four of 12 developing MENA countries with at least one international poverty rate also report shared prosperity, less than one-third of all countries, and much lower than the 80 percent of ECA countries that report shared prosperity.

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[10] Surveys being incomparable could be caused by improvements in survey design or methodology.

Figure 7. Shares of countries reported and not reported in the global shared prosperity database across regions, circa 2012-2017
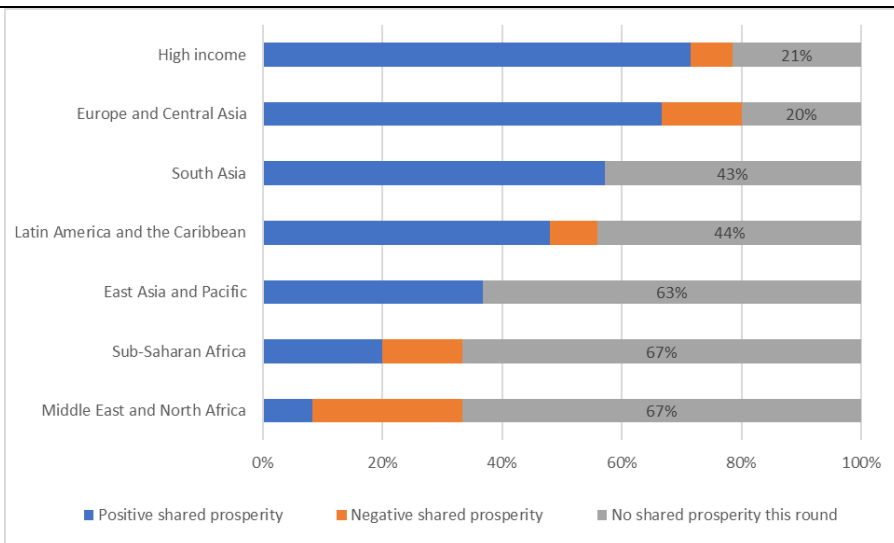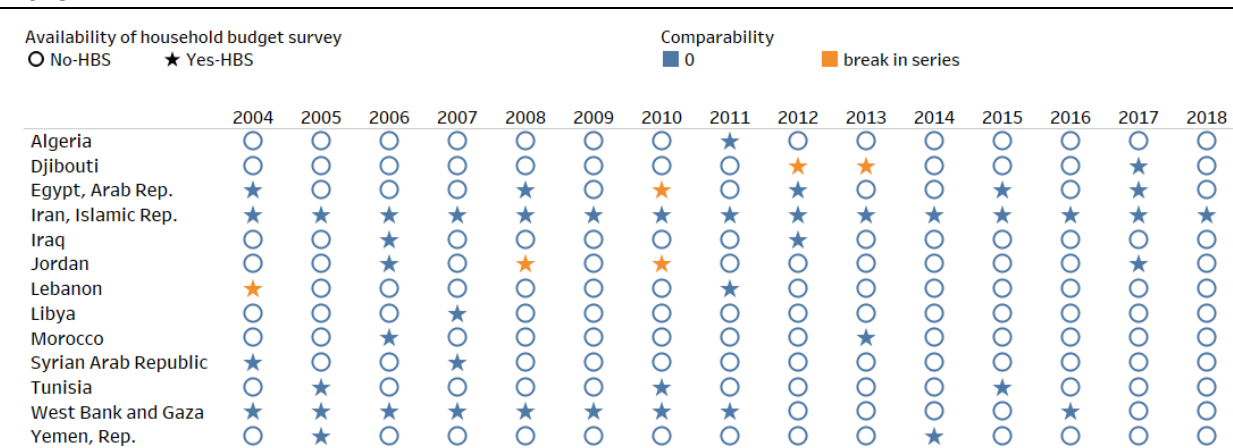

Source: PovcalNet and global shared prosperity database (2012-2017) accessed in May 2020, authors' calculation.
Note: The shares are calculated only for countries with at least one poverty numbers in PovcalNet.

Country-level picture

Figure 8 shows interruptions in the poverty series due to incomparable estimates. Comparability problems exist in four MENA countries—Djibouti, Egypt, Jordan, and Lebanon. In another five countries, too few surveys exist, or surveys are too far apart to estimate shared prosperity. This limits the World Bank's ability to track the regional poverty rate over time, not just national poverty rates.

Figure 8. Comparability of monetary poverty estimates poverty in the MENA region by countries, 2004-2018

Availability of household budget survey   O No-HBS   ★ Yes-HBS
Comparability   ■ 0   ■ break in series

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Algeria	O	O	O	O	O	O	O	★	O	O	O	O	O	O	O
Djibouti	O	O	O	O	O	O	O	O	★	★	O	O	O	★	O
Egypt, Arab Rep.	★	O	O	O	★	O	★	O	★	O	O	★	O	★	O
Iran, Islamic Rep.	★	★	★	★	★	★	★	★	★	★	★	★	★	★	★
Iraq	O	O	★	O	O	O	O	O	★	O	O	O	O	O	O
Jordan	O	O	★	O	★	O	★	O	O	O	O	O	O	★	O
Lebanon	★	O	O	O	O	O	O	★	O	O	O	O	O	O	O
Libya	O	O	O	★	O	O	O	O	O	O	O	O	O	O	O
Morocco	O	O	★	O	O	O	O	O	O	★	O	O	O	O	O
Syrian Arab Republic	★	O	O	★	O	O	O	O	O	O	O	O	O	O	O
Tunisia	O	★	O	O	O	O	★	O	O	O	O	★	O	O	O
West Bank and Gaza	★	★	★	★	★	★	★	★	O	O	O	O	★	O	O
Yemen, Rep.	O	★	O	O	O	O	O	O	O	O	★	O	O	O	O

Source: Authors' compilation.
Note: If survey period bridges two years, the first year serves as a survey year.

5. How to close the data gap?

Closing the data gap when surveys exist or can be collected

The World Bank tries to play an active role in promoting access to household budget surveys. If data sharing is inhibited by lack of experience or capacity, governments can benefit from the World Bank's experience in anonymization and protecting sensitive information; practices of data sharing from around the world that establish rules that govern microdata use and appropriate citation. The World Bank can provide training on preparation of metadata under the Data Documentation Initiative (DDI), an international standard for describing surveys. The World Bank should help support prioritization and advocate for these types of technical assistance (TA) to national statistics offices.

The World Bank can also play a role in promoting the value of open data by facilitating exchange of ideas and experiences within the region and beyond. Inviting leaders in the field to join regional workshops or conferences can help. The World Bank organized such a conference at the Centre for Mediterranean Integration (CMI) in 2016. Keynote speakers and high-level participants from national statistics offices across MENA discussed the challenges involved in collecting and sharing micro-data for monitoring welfare and for evidence-based policy making.[11]

The World Bank also provides TA and funding to help countries conduct HBSs and measure poverty. This TA is typically offered through country-level programs, drawing on long-established country engagements. In several notable examples in MENA, World Bank collaboration with country statistical agencies was very fruitful and resulted in the dissemination of HBSs and publication of national poverty rates. These examples include TA on household surveys in Djibouti, Iraq, Jordan, West Bank and Gaza, and Yemen and on poverty measurement in Egypt, Tunisia, and Lebanon.

Collecting new HBS data and enhancing data sharing are very different in terms of costs. Given the analysis above, collecting new HBS data is more of a priority in MENA than is irregular poverty measurement. Nevertheless, data sharing should be an indispensable part of any international organization's data collection effort.

If collection of a new household budget survey is limited by lack of funds, statistical agencies may consider using the methodology developed by the World Bank and called "Survey of well-being via instant and frequent tracking or SWIFT 2" (Yoshida et al. 2015). The main idea behind this method is the following. Instead of implementing a survey that collects a large sample of consumption data, the statistical agency can collect a nationally representative subsample of both consumption and non-consumption data and a much larger sample of non-consumption data only. Using the first sub-sample, which includes both consumption and non-consumption data, imputation models can be developed, and consumption can be imputed into each household in sub-sample 2.

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[11] Atamanov and Krishnan (2016).

<u>Closing the data gap when surveys cannot be collected</u>

Measuring monetary poverty by survey-to-survey imputation[12]

Many countries operate in an environment where household consumption data are partially missing. This includes situations when: i) consumption data are available at one point in time but are not available in the second point in time, or ii) situations when consumption data exist in all points in time but are not comparable. "Imputation" is the key method to provide poverty estimates in the absence of consumption data.

<u>Method</u>

Measuring monetary poverty is possible only when information about consumption or income is available. When consumption data are not comparable across two survey rounds or do not exist in one of the periods, (survey-to-survey) imputation methods can be used. The necessary condition is availability of at least one HBS that includes consumption data. Key to the survey-to-survey imputation is the estimation of a model that explains consumption or income as a function of different social-economic and geographic characteristics for the same year consumption or income data are available. This model is then used to predict consumption in the second year of the survey, using the same explanatory variables. As a result, each household in the second year will get "imputed" consumption data, making it possible to construct a poverty rate. Detailed technical reviews of the survey-to-survey imputation methodology can be found in Dang et al. (2014) and Dang et al. (2019).

Several countries applied this methodology in the MENA region. Dang et al. (2004) used Jordan's Household Income and Expenditure (HIES) surveys from 2008 to 2010 to impute consumption to the Labor Force Survey during the same period. They validated the results using actual poverty rates from the HIES. The results were encouraging, with imputation-based poverty estimates not showing statistically significant differences from true poverty rates.

Douidich et al. (2013) used the method in Morocco, and Cuesta and Lara Ibarra (2017) simulated poverty in Tunisia using household budget and labor force surveys (LFSs). Using the latest available HBSs to impute consumption and calculate poverty using LFSs in each case, the authors found that the approach accurately reproduced actual official poverty statistics.

<u>Data requirements and pitfalls</u>

Survey-to-survey imputation methods rely on several key assumptions, which may not necessarily hold—a fact that should be taken into consideration before applying them (Dang et al. 2014):

First, the relationship between consumption and other household characteristics in the household consumption survey used in the base period is assumed to remain stable over time. This assumption is not likely to be accurate in countries experiencing structural changes, such as those that occur during conflict or due to a significant economic shock. Assuming stability of household characteristics over time

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[12] Here we focus on the methods which allow getting missing consumption at the household level, but there is another method to get missing poverty rate at the aggregate level by using forecasting techniques. This method is used by the World Bank to track the corporate goal of reducing extreme poverty. The method and its shortcomings are discussed in the annex.

may also not hold in cases where there is a long gap between the base year and the year for which consumption is imputed.

Second, it is necessary for the two surveys to have comparable designs, such as being drawn from the same sample frame. However, very few studies explicitly discuss this assumption and rarely test its validity.

Lastly, it is important to ensure that there are enough explanatory variables with similar distributions across surveys. This is not always the case and very often HBS and LFSs collect different information and ask questions differently. Thus, Newhouse et al. (2014) demonstrate how survey-to-survey imputation failed in Sri-Lanka where wording of questions and survey designs were different in the HBS and the LFS.

This said, survey-to-survey imputation methods are feasible in some MENA countries beyond those listed above. For example, Jordan, Egypt, and the West Bank and Gaza collect annual LFSs that can be used to impute welfare in years in which HBSs are either not collected or not readily shared (see Figure 9 listing existing LFSs in MENA). In countries with no LFSs, we can impute welfare by collecting answers to a small set of questions on poverty correlates using small or specially-designed surveys. However, for imputation methods to perform well, the most recent consumption survey should be up-to-date and adequately reflect current welfare patterns, which is not the case in Algeria, Lebanon, Libya, the Syrian Arab Republic, and Yemen.[13]

Figure 9. Availability and access to the labor force surveys in the MENA region

	Data_availability O no ✔ yes					Access to data for the World Bank ▢ no data ■ no ■ yes								
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Algeria	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	O	O	O	O
Djibouti	O	O	O	O	O	O	O	O	O	O	O	O	O	O
Egypt	O	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	O
Iran	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
Iraq	O	O	O	O	O	O	O	O	O	O	O	O	O	O
Jordan	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
Lebanon	O	O	O	O	O	O	O	O	O	O	O	O	O	✔
Morocco	O	O	O	O	O	O	O	O	O	O	O	O	O	O
Tunisia	O	O	O	O	O	O	O	✔	✔	✔	O	O	O	O
West Bank and Gaza	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
Yemen	O	O	O	O	O	O	O	O	✔	O	O	O	O	O

Source: Authors' compilation.

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[13] The COVID-19 outbreak may affect substantially the feasibility of imputation though, as it can challenge the assumption about stability of coefficients. This just another reason why new household budget surveys shall be collected in countries where it is possible.

Measuring other indicators of well-being

To track welfare in countries without household consumption surveys, one can resort to using indirect measures, either non-monetary indicators or non-traditional surveys.

Multidimensional poverty index (MPI)

Many countries have developed "multidimensional poverty indexes" (MPI) to complement existing monetary poverty statistics and provide a more comprehensive perspective on poverty. Expenditure measures may not accurately assess the cost of some goods and services not obtained through markets, thus prices do not accurately reflect their value. Examples of such goods and services include a clean environment, a secure community, public education and health. Measuring multidimensional poverty can be viable for tracking well-being were consumption data are missing.

Method

The method for calculating MPI, briefly described below, is based on Alkire and Foster (2011). The Commission on Global Poverty, led by Sir Tony Atkinson, recommended the method to measure global non-monetary poverty.

The Alkire and Foster method (AF) consists of two steps. The first is to create a deprivation profile by comparing individuals or households to the respective deprivation cut-off point for selected indicators. The second step is to apply weights (which sum up to "1" or to 100 percent) to each of the indicators, and to sum them for each person to establish a deprivation score of weighted percentage of deprivations. Individuals are then identified as multidimensionally poor if the weighted sum of their deprivations is higher or equal to the poverty cut-off point (United Nations Development Program, 2019).

Data requirements and pitfalls

Constructing MPIs is data-intensive and requires information on each deprivation for all households. Therefore, information should be based on micro-level data and should come from one source. This is challenging because it is not easy to find microdata with information on all dimensions of non-monetary poverty. Multiple Indicator Cluster Surveys (MICS) and Demographic and Health Surveys (DHS) collect comprehensive data on the health status of women and children but have limited employment data and no consumption data (UNDP, 2019).[14]

The latest regional report on Arab multidimensional poverty (UN, 2017) covered seven countries and used, in most cases MICS, DHS, and Arab Family Health Project data. It did not construct MPI for Djibouti, the Syrian Arab Republic, Libya, and Lebanon because of a lack of recent data. The West Bank and Gaza was excluded due to unique problems related to blockade and movement restrictions. Table 4 presents

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[14] Many countries base MPIs on household budget surveys, which allows measuring both monetary and non-monetary poverty. However, as noted in World Bank (2018), many surveys measure access to services and rarely the quality of services. Adding questions to measure quality of services may increase survey burden and jeopardize ability to monitor monetary poverty; so, there are trade-offs between the decision to collect monetary and/or non-monetary information.

the selected dimensions and indicators for the region. The Arab MPI was based on three dimensions: education, health, and living conditions.

Table 4. Dimensions and indicators of deprivation for household poverty in Arab multidimensional poverty index

Dimensions	Deprivations
education	Years of schooling
	School attendance
health	Child mortality
	Nutrition
	FGM/early pregnancy
Living conditions	Electricity
	Sanitation
	Water
	Floor/roof
	Cooking fuel
	Overcrowding
	Assets

Source: Authors' compilations based on UN (2017).

Constructing the MPI using MICS or DHS could potentially provide an important alternative to monetary poverty in MENA countries where collection of HBSs is not possible, or where existing surveys are old. Figure 10 shows the most recent years for HBS, MICS, and DHS in MENA countries. Algeria, Iraq, the West Bank and Gaza and Tunisia could benefit from more recent MICS data compared to their outdated HBSs. However, the situation in the most data-deprived countries, such as the Syrian Arab Republic or Libya, cannot be improved given that there are no recent DHS or MICS surveys. In addition, the MPI, depending on deprivations selected, may not be very sensitive to economic changes in the country. For example, number of years at school may not change quickly during the economic crisis.

It is also important to remember that tracking multidimensional poverty over time requires comparable DHSs or MICSs. Comparability also requires identical definition of deprivations in the different years, including definitions of indicators, cut-offs, and weights. Finally, countries will have to conduct DHSs and MICS regularly and frequently, which is not always the case. For example, MICSs were conducted only every six to seven years in the MENA region.

Besides availability of microdata, several important technical issues should be addressed when constructing MPIs. The first relates to applicable population—the group of people for whom an indicator is relevant. Very often, MPIs define deprivations only for a group of people. For example, MPIs measure school enrollment typically for children at the age of compulsory schooling, and measure employment for particular adults. As a result, there are inapplicable households. A decision should be made on how to treat these cases. One widely used option is to assume that these households are not deprived, a conservative approach that may underestimate poverty. The World Bank (2019) takes a different approach by shifting the weight for the missing indicator to other indicators within the dimension so that each dimensional weight remains unchanged.

Figure 10. Latest year of household budget survey, MICS and DHS in MENA countries
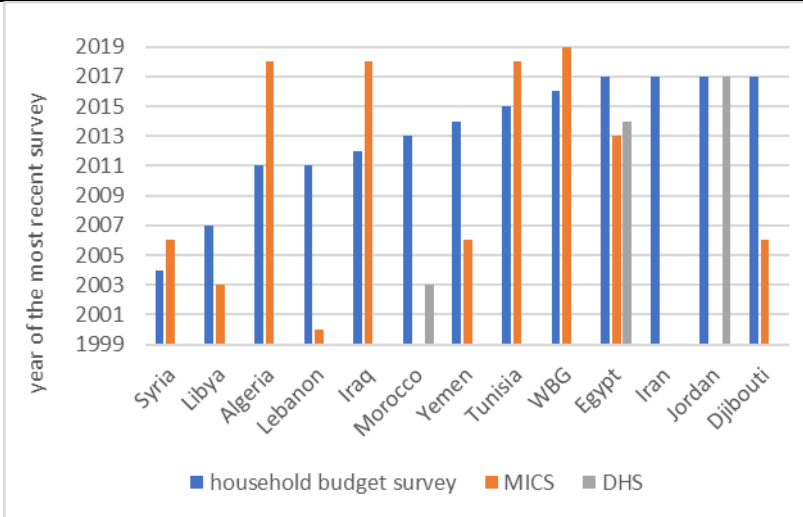
Source: Authors' compilation.

The same decision should be made in cases where missing information prevents construction of the indicator. For example, if information about schooling is missing and an indicator cannot be constructed, a household can be considered as non-deprived, deprived, or can be dropped from the analysis.

Asset/wealth index

Asset or wealth indexes are a popular substitute for household consumption data since almost all household surveys collect information on household assets and housing characteristics. Here we briefly discuss the method and its key assumptions and limitations.

Method

The key assumption underlying asset or wealth indexes is that household assets and housing characteristics correlate with the long-term wealth of a household. The question is how to aggregate this information into one index to be able to rank households.[15] There are different ways to construct an aggregate measure of assets. One of the most popular methods is based on Filmer and Pritchett (2001), who proposed a statistical technique using "principal components analysis" (PCA) to determine the weights for different assets in the index.

The principal components method extracts from a set of variables those few orthogonal linear combinations of the variables that capture common information most successfully. The first principal component of a set of variables is the linear index of all the variables that captures the largest amount of information common to all of the variables. The current practice is to retain the first principal component as the asset index. Generally, a variable with a positive factor score is associated with higher socio-economic status; conversely, a variable with a negative factor score is associated with lower socio-economic status.

Data requirements and pitfalls

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[15] Ideally, one would want to use prices as weights for different assets, but these are not available.

Asset data collection is relatively easy and cost-effective. Many household surveys, including DHSs and MICS, collect asset and housing conditions through appropriate modules. Using assets minimizes measurement problems associated with income and consumption-based indicators, such as recall bias and seasonality. [16] Estimation of a wealth index using the PCA method is rather straightforward, and there are several ready-to-use commands in statistical and econometric software to implement the method.

Despite its simplicity, important limitations in using asset indexes to measure and track well-being over time should be considered. Several papers have demonstrated that correlation between asset indexes and consumption poverty is low (for instance, Filmer and Scot, 2008). The discrepancy may be stronger in the poorest areas where households spend larger shares of their budgets on food. Nevertheless, many still consider asset indexes useful for welfare analysis when consumption data are not available.

Using asset indexes across heterogenous settings and over time has concerns (Harttgen et al., 2013). First, preferences for some assets, such as mobile phones and flat-screen TVs, may increase over time and become part of "normal" living conditions; this may cause incomparability between asset indexes over time. Second, asset indexes do not consider age or quality of assets; some households may accumulate old assets, therefore overestimating a rise in assets. Third, in many countries, access to some assets, such as electricity or clean water, is a result of public policies and does not represent a reliable proxy measure for actual household consumption.

Constructing asset indexes using MICS or DHSs could represent an important alternative to monetary poverty in MENA countries where existing consumption surveys are very old. However, as shown in the previous section, countries do not collect MICS or DHSs frequently in the region and the problem of outdated data remains. In addition, correlation between assets and monetary poverty could be poor in the region, especially in conflict-affected countries where asset ownership may not highly correlate with poverty.

Food security and subjective well-being

This section focuses on two alternatives to non-monetary measures of well-being: food security and subjective well-being. Phone and public opinion surveys often collect these measures and each type of survey is discussed below.

Phone surveys

Method

Remote forms of data collection, such as mobile and fixed-line phone surveys, are particularly effective in two contexts: i) settings where it is not safe or possible to perform face-to-face surveys, and ii) settings needing high-frequency data collection (Hoogeveen et al., 2014). Both settings are prevalent in MENA. Nearly 30 percent of the region's population is exposed to either conflict or persistent violence, and the entire region is particularly vulnerable to political, climate, and other types of shocks where welfare monitoring at higher frequency could better inform policy making. During the COVID-19 pandemic, many

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[16] Households may have difficulties in remembering all expenditures they made in the past leading to recall bias. Some expenditures/consumption are also seasonal fluctuating across time. Therefore, data collection should ideally last the whole year to properly capture the seasonal variation.

statistical offices will have to rely on phone surveys to collect information from households on the crisis's impact while avoiding any face-to-face contact.

Ideally, a phone survey uses a nationally representative sample frame, where, if possible, the first round is an (existing) face-to-face survey. Once completed, researchers conduct follow-up phone interviews at regular monthly, quarterly, or other intervals. The survey output contains repeated welfare observations for each household, often before and after welfare shocks caused by violence, displacement, drought, or other things.

Baseline face-to-face interviews serve two primary purposes. First, to construct more traditional household welfare metrics—for instance, poverty—and then follow up with short questions more suited for a phone interview regarding changes in welfare. Second, for households without phones, one can be provided so that follow-up interviews can be truly nationally representative, as opposed to only representing the population with phone access (see for example, Dabalen et al., 2016).

When face-to-face interviews are not possible, as in the Syrian Arab Republic or during the COVID-19 epidemic, survey firms or statistical agencies could conduct phone surveys using a list of phone numbers representative of the population with access to a phone. Such a list can be acquired from phone numbers collected in the last nationally representative survey conducted in a country (see for example, Himelein et al., 2015). Alternatively, if such a list either does not exist or is outdated, partnering with mobile phone companies can generate a sample frame.

Lastly, when a list of the phone-using population is not available, surveyors can collect phone numbers via random digit dialing (RDD). Survey firms have algorithms to randomly dial phone numbers until a household answers, after which the household is offered the opportunity to complete a survey. The World Food Programme (WFP) used this approach effectively in Yemen, completing surveys of 2,400 households every month over the entire course of the conflict in that country (WFP, 2018).

Data requirements and pitfalls

There are two primary drawbacks to the telephone survey approach. First, phone interviews can only accommodate relatively straightforward questions and have to be much shorter than face-to-face interviews. For these reasons, phone interviews cannot produce more traditional welfare metrics, such as poverty. Straightforward indicators of deprivation—such as lack of access to food, school, sanitation, and medical care—are more suitable for phone data collection.

A second drawback to the phone survey approach is difficulty in obtaining a representative sample of phone numbers. Particularly when face-to-face surveys are not possible, surveyors must settle for a survey that only represents the population with access to a phone and covered by a phone network. In the absence of readily available registries of phone numbers (e.g. from past face-to-face surreys), it may be difficult to obtain phone numbers of the phone-using population once a large shock has occurred. Thus, in many cases, surveyors rely on RDD-based surveys, which introduce selection bias for certain outcomes (see for example., Abraham et al., 2009).

In MENA, where phone penetration rates are high, phone surveys can play a very important role in measuring (subjective) well-being. The phone survey approach is particularly useful in conflict-affected countries—such as Iraq, the Syrian Arab Republic, Yemen, and Libya—where it is necessary to rely on remote data collection methods. Phone surveys can also be useful in other MENA countries where high-

frequency data can supplement infrequent HBSs to help identify rapid political and social-economic changes. For example, Lebanon and the West Bank and Gaza could benefit from this type of data collection given the high frequency of shocks people in each country face.

Public Opinion Surveys (Gallup, Arab Barometer, World Values surveys)

<u>Method</u>

Some firms and organizations perform household surveys at a higher frequency than national statistical offices. The Gallup World Poll (GWP) conducts surveys every year in nearly every country, for example. Importantly, this includes surveys in some very challenging settings, such as Yemen. These surveys can supplement traditional household surveys to better understand how welfare is evolving in data-scarce environments.

Each type of organization has its own sampling strategy in each individual country and year. For example, the GWP outsources sampling and actual surveying to survey firms in each country. Depending on the capacity of the firm and the security situation, the surveys can be either face-to-face or conducted via mobile phone. In each year, the GWP surveys 1,000 nationally representative households. Importantly, each survey is comparable across countries and can be particularly useful for region-wide analysis.

One problem with public opinion surveys is that they are short, with questions typically focusing on subjective welfare and household opinions. However, each survey collects information on employment and access to food and shelter, all of which strongly correlate with poverty. We can use these data to identify welfare trends in a country over time, even in settings with no traditional welfare metrics.

<u>Data requirements and pitfalls</u>

There are three primary drawbacks to using public opinion surveys as a source of welfare information. First, similar to phone surveys, one cannot construct traditional welfare metrics, such as poverty. Furthermore, the survey collects very little information on household characteristics, location, and living conditions. Given these important gaps, these surveys are best used to supplement household surveys. That said, in countries with little-to-no information, these surveys can provide at least some welfare information to policy makers and researchers.

 Second, given the lack of uniform sampling both across countries and within a country over time, it is difficult to identify how representative each survey is of the entire population. Related to this, the quality of the survey firms subcontracted to perform the surveys is unknown. Combined, these two factors can make welfare estimates "noisier" (less accurate and varying more) compared to welfare metrics from traditional data sources, and subsequently make it difficult to interpret welfare levels and how they change over time.

Table 5. Availability of non-traditional public opinion surveys in the MENA region with open access: Arab Barometer and World Value Surveys during 2010-2019

Survey	Countryname	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Arab Barometer	Algeria		+		+			+			+
	Bahrain										
	Djibouti										
	Egypt, Arab Rep.		+		+			+			+
	Iran, Islamic Rep.										
	Iraq		+		+						+
	Israel										
	Jordan	+		+				+			+
	Kuwait					+					+
	Lebanon	+		+				+			+
	Libya					+					+
	Malta										
	Morocco				+			+			+
	Oman										
	Qatar										
	Saudi Arabia		+								
	Syrian Arab Republic										
	Tunisia		+		+			+			+
	United Arab Emirates										
	West Bank and Gaza	+		+				+			+
	Yemen, Rep.		+		+						+
World Values Survey	Algeria					+					
	Bahrain										
	Djibouti										
	Egypt, Arab Rep.			+							
	Iran, Islamic Rep.										
	Iraq				+						
	Israel										
	Jordan					+					
	Kuwait					+					
	Lebanon				+						
	Libya										
	Malta										
	Morocco		+								
	Oman										
	Qatar										
	Saudi Arabia										
	Syrian Arab Republic										
	Tunisia										
	United Arab Emirates										
	West Bank and Gaza				+						
	Yemen, Rep.					+					

Source: Authors' compilation from Arab Barometer and World Values Survey websites.

Third, gaining access to these surveys is expensive. Although some are free—for example, the Arab Barometer, World Values Survey—the standard cost for the GWP is $10,000 per year for each country. Furthermore, since multiple years are needed to make valid welfare metrics inferences, the cost to use GWP data can escalate quickly for each country.

In summary, public opinion surveys can help track changes in subjective well-being in MENA countries and help with cross-country comparisons. However, these types of surveys are an imperfect substitute for monetary and non-monetary indicators of well-being from traditional representative household surveys.

Measuring well-being by using "big data"

This section describes non-traditional sources of data, not obtained by sample surveys, which can sometimes be used to measure well-being.

Administrative data

<u>Method</u>

Administrative records are data collected for carrying out governmental programs or processes. These include:

- Records related to regulation of the flow of goods and people across borders.
- Data from legal requirements to register events (births, marriages, among others).
- Benefits and obligations administration records (taxation, pensions, health insurance).
- Records related to administration public institutions (schools, health institutions, prisons).
- Data arising from government industry regulation (banking, transportation, telecommunications).
- Records from electricity, water services or telephony utilities (Brackstone, 1987).

More broadly, administrative data can also include private companies' records or any entities' historical data on their assets, people, or resources. Schools, hospitals, and other organizations routinely collect data to serve students, clients, or stakeholders. In other words, administrative data cover a wide variety of areas, and are relatively inexpensive to collect since they are already available or captured as part of governmental or private companies' processes.

Using administrative data also minimizes burdening participants with more surveys and avoids some data quality loss due to misreporting. Evidence shows that an important source of misreporting is the unwillingness to provide socially undesirable answers. Stigma is often associated with participation in welfare programs, for instance (Celhay, Meyer & Mittag, 2018). Criminal records or violence data are other examples of data that can be difficult to obtain with a survey or other method.

The versatility and availability of administrative data allows researchers to address a variety of important questions and areas, including long-term effects of past policies. Administrative data can provide accurate details related to policy costs and benefits (Penner & Dodge, 2019). For example, evaluators stop collecting data at the end of their study in most impact evaluations. However, participants of policy interventions or projects (the treatment group) remain captured in administrative records, which can provide valuable information to estimate long-term effects.

Evidence proving the value of administrative data is vast. Chetty et al. (2011) found evidence on income effects of having an experienced kindergarten teacher and higher-achieving classmates; and Aizer and Eli et al. (2016) found that cash transfers to poor families can have positive educational, mortality, and income outcomes on the families' children decades after the transfers. As stated before, administrative data do not need to be supplied by government; there is a long tradition of case studies using administrative records from company human resources departments, for instance. Fernandez and Greenber (2013) found evidence of gender and race inequality in the hiring processes of companies; and Fernandez and Rubineau (2019) analyzed the impact of network recruitment effects on the gender "glass ceiling" in the biopharma industry.

When administrative records are good quality, they can even be linked to households or other individual-level surveys to add variables to the survey, but also to measure and improve survey accuracy. Davern et al. (2008) used an imputation method to test the validity of self-reported health insurance coverage in survey data; Meyer and Mittag (2019) used administrative data to identify patterns and uncover

significant misreporting by transfer recipients in national surveys; and Nicholas and Wiseman (2010) used administrative records to evaluate and estimate better measures of poverty for social security recipients.

Data requirements and pitfalls

The first pitfall related to use of "big data" is the quality and discontinuity of the data. Administrative records can be severely fragmented. Censuses and surveys rarely change, because the data should allow comparisons over time; if they do change, modifications respond to specific needs. In governmental programs, changes may occur due to legislative, regulatory, or political matters affecting the scope of the data and their use. Furthermore, in some administrative systems, individual records remain at the local source and only aggregate data are assembled centrally. In other systems, data might not even be centralized. Having several institutions or agencies responsible for data can interfere with quality control that a central agency or researcher can impart. In other words, these are obstacles to collection of quality, complete, and continuous data.

Coverage and content represent further drawbacks. With administrative data, target populations, topics, and all specific variables of interest are defined by administrative requirements or purposes. Contrary to surveys were the researcher can design the questions of interest, administrative records offer a limited source of information and variables. For example, when using tax records to analyze businesses or industries, databases need to be complemented with another source to better estimate production statistics (Brackston, 1987).

Administrative records might not be representative of the national population. Most governmental programs cover only a portion of the population with very specific beneficiary characteristics. Records can also suffer from misreporting; for example, tax reports can lack information on the many informal economic actors. Weaknesses in administrative data coverage and content are the main reasons why many empirical studies use data imputation based on surveys, or other alternative sources of data and information on sample populations.

Lastly, another pitfall is access and confidentiality. Depending on the regulatory premises of each country, access to administrative data may be limited to confidentiality-protected aggregate data or to disaggregated individual data. Open governments can be a great source of information, but in many cases data access is limited due to unwillingness of governmental administrations to fully share program beneficiary databases or other information that could hold administrators accountable.

Confidentiality can also prevent governments from providing full access to its records. Since some statistical techniques require individual identifiers to manipulate intermediate data, there could be public privacy concerns related to how databanks could be used against respondents.

Social networks

Method

Communications within an individual´s social network can reveal a lot of information about individual interactions, mobility, and habits that correlate with socioeconomic levels. Bluemenstock, Cadamuro and On (2015) showed that an individual's mobile phone history, for example, can infer socioeconomic status. Furthermore, they showed that it is possible to derive national and subnational wealth estimates from patterns in cellular phone trace data.

These sources of information combined with traditional data allow new approaches for empirical investigation. For example, Blumenstock et al. (2018) combine firms' mobile phone and administrative data with geocoded violent events data to investigate how Afghanistan's private sector reacts to insecurity. Using existing cell phone network data in this case was particularly fruitful because of the unsafe and violent context of the country.

In countries where data availability is constrained, or where data have not been collected, mobile phone metadata can provide important insights into population behavior and characteristics. This source of information not only reveals an individual's intricate social network, but can reveal communications frequency, intensity, directionality, and timing; travel patterns; migration patterns and specific locations; and consumption and expenditure histories with much more frequency than traditional survey information.

Cell phone technology uses base transceiver stations to connect cell phones with the network, and ranges for stations vary from less than 1 km^2 in dense urban areas to more than 3 km in rural areas. Thus, mobile phone data permit a much more disaggregated geographic level of analysis compared to household surveys, which are limited to state or district levels (Soto et al. 2011). In theory, the frequency and locational advantages of mobile phone network data could be combined with new methods for real-time policy evaluation and population monitoring in remote, violent, and inaccessible regions.

Data requirements and pitfalls

While some studies have shown that an individual's footprint can predict her socioeconomic level, and therefore substitute for census or household data (Blumenstock, Cadamuro & On, 2015; Soto et al., 2011), most studies use network data to complement more traditional data sources. For example, Gutierrez, Krings, and Blondel (2013) created a predictive model to extract indicators of wealth, inequality, and segregation from mobile phone data. They suggest that network data sets represent a starting point to understand socioeconomic variables in countries with no resources to conduct large surveys. At the same time, these researchers are also cautious, warning that traditional surveys are still needed to build more accurate models or to assess the quality of mobile phone data.

Data quality can vary according to the specific scope of a study. For example, in the previous Blumenstock et al. (2018) paper using private firms' mobile phone data in Afghanistan, the authors disclaim that registered corporate lines are unlikely to represent all firms, particularly small and informal firms operating outside urban areas. In developing countries, the large size of the informal economy can skew results interpretation. Similarly, mobile phone information is limited to people able to afford a cell phone. Even though mobile phone use is increasingly widespread, it is important to note the limitations of these data sets

A last drawback is related to data availability and individuals' privacy. Since private firms usually operate cell phone networks, it can be problematic to obtain user data due to commercial, ethical, and regulatory concerns. It is hard to estimate the cost of these data sets, but the main obstacle for obtaining them may be regulatory and administrative hurdles. Researchers must prove that they will use the information only for research purposes.

Geospatial data

Method

Economists have used remotely sensed information since at least the 1930s, but digital technology advancements have allowed economists to start taking significant advantage of this source of information (Donaldson & Storeygard, 2016). Geospatial data cover wind speed, night light, precipitation, forest cover, crop choice, economic activities, urban development, building type and size, roads, pollution, beach quality, and many other difficult-to-measure statistics. The advantage of using geospatial data is amplified by the fact that they are usually available at a much higher degree of spatial resolution than traditional data, addressing a problem frequently found in MENA countries.

For example, National Aeronautics and Space Administration (NASA) data on nighttime lights offers a good proxy for settlement patterns and wealth (Henderson, Storeygard, and Weil, 2012). In fact, estimating economic activity using night lights can more reliably approximate real GDP since it accounts for informal economic activity, and does not depend on government infrastructure to measure. Nighttime light data can play a key role analyzing economic activity at the subnational level, especially in countries with poor quality or non-existent information.

Geospatial information has also been used to estimate welfare indicators. This non-traditional source of information not only allows new ways to explore topics, but also proxies for wealth and poverty data. Marx, Stoker, and Suri (2015) used satellite data to detect better-maintained or new roofs as indicators of higher quality housing in Nairobi. Kudamatsu, Persson, and Stromber (2012) studied how weather fluctuations affect infant mortality in Africa. Daytime imagery has even been used to estimate and replace bad quality poverty data in developing countries (Xie et al., 2016). As with phone surveys, geospatial data have also proved to be an excellent option in persistent conflict and unsafe zones, or for data on illegal and informal activities not usually reported. For example, remote satellite sensing can capture spectral reflectance of different crops, thereby allowing calculation of land surfaces devoted to poppy cultivation (Lind, Moene, and Willumsen, 2014).

Data requirements and pitfalls

There are three primary pitfalls related to use of geospatial data. The first is related to cost. Although much of the sensor-captured data on land cover, forest, and airborne pollution are public and free, some disaggregated data provided by public entities, or specific data provided by private firms, are costly. For example, access to the global annual cloud-free nighttime lights database costs $70,140 dollars, and the global nighttime light monthly increments cost $7,665 per year. Depending therefore on a study's time frame type of information needed, geospatial data costs can escalate quickly.

The second drawback is data complexity and the skills needed for processing. Earth's land area can be subdivided into hundreds of trillions of one-meter cells, making such high-dimensional data difficult to model even with linear functions (Donaldson & Storeygard, 2016). Also, satellite data can often be highly correlated among nearby units. Whether spatial dependence appears as a dependent or independent variable, statistical inference should be taken with caution and adjustments made to correct potentially biased coefficients.

The third pitfall is related to ethical concerns. While approaches have taken advantage of available data, such as nighttime lights, to measure variables such as welfare in developing countries (Donaldson & Storeygard, 2016; Henderson, Storeygard & Weil, 2012), or building type and size information (Marx, Stoker, and Suri, 2015), using very high-resolution imagery might raise individual privacy and regulatory concerns.

In the MENA context, geospatial data can be particularly useful in conflict affected countries to prioritize interventions aiming to provide basic services. For welfare measurement, geospatial data can help design surveys by providing population estimates and help create sampling frames in countries where this information is obsolete or the displaced population is large, such as in Iraq, Lebanon, Djibouti and others (Hoogeveen and Pape, 2020). Finally, geospatial data can improve modeling for consumption imputation for poverty maps (small area estimation).

Summary of relevance and feasibility of different methods

To summarize the discussion of methods/data to fill HBS data gaps, table 6 ranks approaches from "1" to "3" indicating both relevance and feasibility in each country context. Lower numbers indicate the highest relevance and feasibility. We put "0" when the method is irrelevant or not feasible in a particular country.

Table 6. Ranking different methods and types of data for measuring well-being in the MENA countries

	measuring monetary poverty		measuring non-monetary poverty or use as auxiliary data to measure well-being			
	collecting household budget survey	Imputation	MPI/asset index	Food security/subjective well-being	Administrative data	Other big data
Algeria	1	0	2	2	3	3
Djibouti	1	1	0	2	3	3
Egypt, Arab Rep.	1	1	0	2	3	3
Iran, Islamic Rep.	1	2	2	2	3	3
Iraq	2	1	1	1	2	2
Jordan	1	1	2	2	2	2
Lebanon	1	0	1	2	2	3
Libya	0	0	0	1	2	2
Morocco	1	0	0	2	2	3
Syrian Arab Republic	0	0	0	1	1	1
Tunisia	1	2	0	2	2	3
West Bank and Gaza	1	1	2	2	2	3
Yemen, Rep.	0	0	0	1	2	1
Source						

Algeria, for example, conducted its latest HBS in 2011, its latest labor force survey (LFS) in 2014, its MICS in 2017, and its Arab Barometer in 2019. Using this information, we ranked different methods and data for measuring well-being the following way. "Conducting a new household budget survey" as a top priority, and calculation of an MPI/asset index and measuring subjective well-being as second-best options. Alternatively, we note that imputation is not feasible because the existing HBS is too old. Using administrative and big data can help, but it is unclear how we might access credible welfare information.

Overall, collecting new HBS data is a top priority for nine of the 13 countries. Imputation is feasible in a number of countries for years they have not conducted HBSs. As expected, conflict affected countries (highlighted by grey color in Table 6) use different strategies to measure well-being, with most relying on non-traditional methods and data.

6. Conclusions

Household budget surveys (HBSs) are crucial to establish poverty monitoring systems and to design evidence-based policies. This paper summarized microdata challenges the MENA region faces related to measuring well-being and discussed ways to overcome these challenges.

Despite improvements in public access to microdata, data availability is poor in the MENA region, comparable to the much poorer Sub-Saharan Africa (SSA), and lags the rest of the world. Lack of data timeliness further compounds the availability challenge: seven of the 13 developing countries in MENA had fewer than three surveys between 2004 and 2018. In many countries, the most recent surveys were conducted between 2006 and 2014, making their data outdated. HBSs also become outdated for other reasons: some countries take an exceedingly long time between data collection, producing and publishing a poverty estimate, and sharing the data with organizations such as the World Bank for use in international poverty comparisons.

As a result of these issues, measuring monetary poverty in MENA is complicated, at the country and at the regional level. Inability to measure poverty and other social-economic characteristics on a regular basis negatively affects national decision makers and hinders the ability to track progress against the Sustainable Development Goals (SDGs). Outdated surveys result in outdated consumption distributions, leading to inaccurate poverty monitoring and the exclusion of countries from global and regional poverty counts.

The priority for filling data gaps to measure well-being in MENA should be (i) improving access to existing HBSs and, (ii) a more regular collection of HBS data. International organizations, including the World Bank, can play a supportive role by providing technical assistance (TA) and sharing expertise in data collection, poverty measurement methods, microdata anonymization, and data sharing practices. International organizations can also provide funding or co-finance microdata collection in countries with limited resources.

If data collection is not possible, one can turn to data imputation techniques to obtain poverty estimates. This approach requires at least one up-to-date consumption survey and a non-consumption survey that collects similar individual and household socio-economic characteristics. This approach should be tested in MENA countries with established regular collection of labor force surveys (LFSs). The ongoing COVID-19 pandemic can create a structural break in consumption series and may limit the possibility of imputation, calling for collection of new household budget surveys when lockdown is over.

If collection of new HBSs is not possible, and imputation is not feasible either, measuring non-monetary indicators of well-being using non-traditional surveys can be considered. For example, multidimensional poverty indexes (MPIs) can be used to track non-monetary dimensions of poverty. However, constructing MPIs is data intensive and requires information on each deprivation for all households. Multiple Indicator Cluster Surveys (MICS) and Demographic and Health Surveys (DHS) are often used for this purpose, but there are few countries in MENA where these surveys are more up to date than HBS surveys.

High phone penetration in MENA offers another alternative. Phone surveys can be valuable in conflict settings or other situations (COVID-19) when face-to-face data collection is not possible, and where the population has experienced large and sudden shocks and rapid information is needed. A key drawback of

this method is that the surveys typically represent only the phone-using population. In addition, this mode of data collection allows asking only a short set of questions.

Using "big data" in the MENA region—such as administrative records, geospatial information, and social networks—can help to measure well-being without requiring burdensome face-to-face interactions. This can be particularly useful when collecting traditional data through sample surveys is not possible. However, the main disadvantage of "big data" approaches is that researchers cannot control the population covered, and the data can overlook populations of interest or introduce welfare estimation biases. Restrictions on data access and confidentiality related to administrative records can be further serious constraints. However, mixing "big data" approaches with traditional surveys has significant potential to improve poverty measurement.

In summary, the MENA region is facing substantial problems related to the availability and timeliness of HBSs necessary for regular welfare measurement. Priority for the region should be to regularly collect consumption survey data and to improve access to, and the quality of, existing surveys. Where conducting more HBSs is not feasible—especially in violence and conflict affected situations—using alternative non-consumption surveys and imputation techniques, and/or conducting phone surveys, may be considered as a second-best solution. Using "big data" opens possibilities to measure well-being, but researchers should use them cautiously and in conjunction with traditional surveys, where possible.

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Annex

A.1. Measuring regional poverty in MENA: Issues and solutions

This section focuses on particular data issues associated with measuring regional poverty rates in the MENA region. The World Bank's regional poverty numbers are typically reported for the common reference year - currently 2015.

Population coverage

To report regional poverty rates, country surveys should cover more than 40 percent of the total regional population. Additionally, surveys should have been conducted within two years of the reference period (either before or after). In our context, this would imply that any survey conducted before 2016 will not be counted in the population coverage for 2018, and any survey before 2013 will not be counted for population coverage for 2015. The current population coverage for 2018 estimates in MENA is about 51 percent and is based on the following countries: Djibouti, the Arab Republic of Egypt, the Islamic Republic of Iran, and West Bank and Gaza[17] (Table A1 and Figure A1). It dropped substantially from 68 percent in 2015, the reference year.

For illustrative purposes we also demonstrate the coverage if the most recent survey from Egypt is not available or not accessible. The coverage will drop far below the required level of 40 percent for the MENA regional poverty rate to be reported. This situation happens because household budget surveys (HBSs) are not conducted regularly in MENA, as discussed.

Table A 1. Population coverage for MNA regional poverty rate in 2015 and 2018 reference years

	actual coverage for 2015 reference year	actual coverage for 2018 reference year	hypothetical coverage for 2018 reference year if most recent survey for the Arab Republic of Egypt (2017) is not available/accessible
Algeria-2011			
Djibouti -2017	+	+	+
Egypt, Arab Rep.-2017	+	+	+
Iran, Islamic Rep.-2017	+	+	
Iraq-2012			
Jordan-2010*			
Lebanon-2012	+		
Morocco-2013	+		
Syrian Arab Republic-2004			
Tunisia-2015	+		
West Bank and Gaza-2016	+	+	+
Yemen, Rep.-2014	+		
Libya			
coverage	68%	51%	23%

Source: PovcalNet as of May 2020 and authors' calculations.
Note: country is included if the survey is conducted within two years of the reference period. * There is more recent survey for Jordan, but it is not allowed to be used for calculation of international poverty rates yet.

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[17] Jordan's most recent survey is not available to be used to measure international poverty.

Figure A1. Most recent accessible to the World Bank microdata used to construct MENA regional poverty rate for 2015 and 2018 reference years.
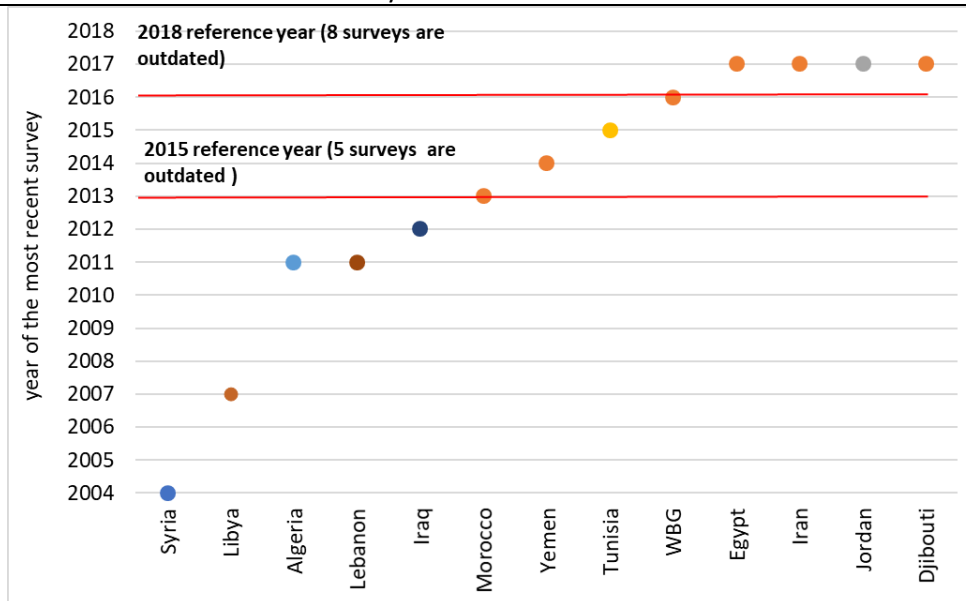
Source: PovcalNet as of May 2020 and authors' calculations.

"Nowcasting"

Usually survey years are earlier than reference years when calculating regional poverty, and survey consumption or income is adjusted by real Gross Domestic Product (GDP) growth rates or household final consumption expenditure (HFCE) per capita. This process is called "nowcasting". For simplicity, it is assumed that inequality remains unchanged. Therefore, accuracy of lined-up numbers will depend on how old the underlying data are, on the accuracy of GDP and HFCE per capita estimates, and on how economic growth relates to household consumption.

This approach may be problematic for MENA where many countries suffer violent conflicts or refugee crises. In these circumstances, imprecise measurement of GDP per capita during conflict and outdated surveys will result in inaccurate poverty estimates. Furthermore, assuming distribution-neutral growth may not hold given substantial socio-economic and political changes in conflict affected countries.

So far there was only one study systematically exploring performance of different nowcasting methods predicting poverty one year ahead based on countries from the Latin American and Caribbean (LAC) region (Caruso et al., 2017). According to the study, nowcasting using distribution-neutral growth produces quite accurate results. Mean absolute error (difference between nowcasted and actual poverty rate) was less than 4 percent, and in a majority of cases errors did not exceed 20 percent. Nevertheless, the results based on LAC, where National Statistical Offices (NSOs) usually release poverty numbers with one year of

lag and microdata quality is very high, may not be applicable in MENA where most of surveys are not collected regularly and many countries experience structural breaks.

One simple exercise estimated international poverty rates for MENA countries using preceding surveys as a base and real GDP per capita growth rates. Figure A2 compares actual and predicted poverty rates. Many countries are away from the 45-degree line, signaling differences between actual and estimated poverty rates. Actual difference in percent and absolute terms is shown in Figure A3. On average, among the selected set of countries the difference is about 32 percent, reaching 130 percent in Iraq in 2012. In some countries, estimation changes the trend (Figure A4). Thus, estimated poverty drops in the West Bank and Gaza in contrast to an increase in the actual poverty rate between 2011 and 2016. Actual poverty dropped in the Islamic Republic of Iran between 2009 and 2013, while estimated numbers show a slight increase in poverty.

Figure A2. Comparing actual and predicted international poverty rates in selected developing MENA countries
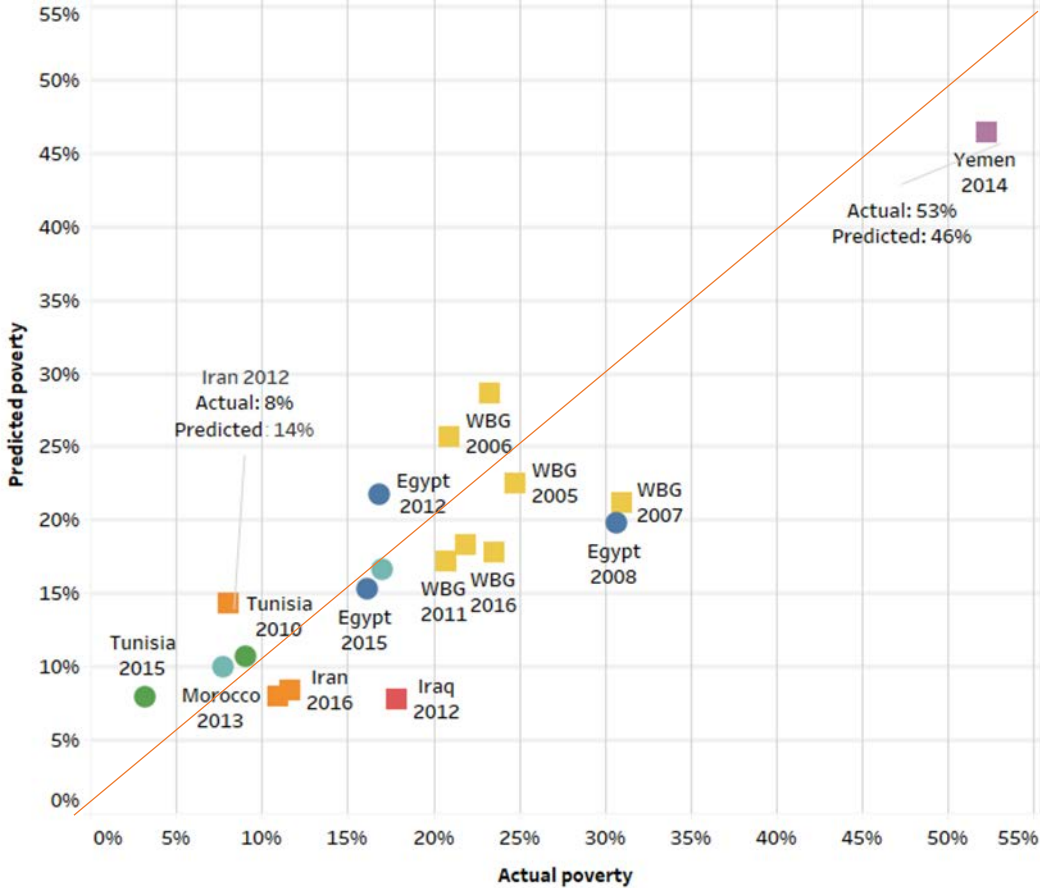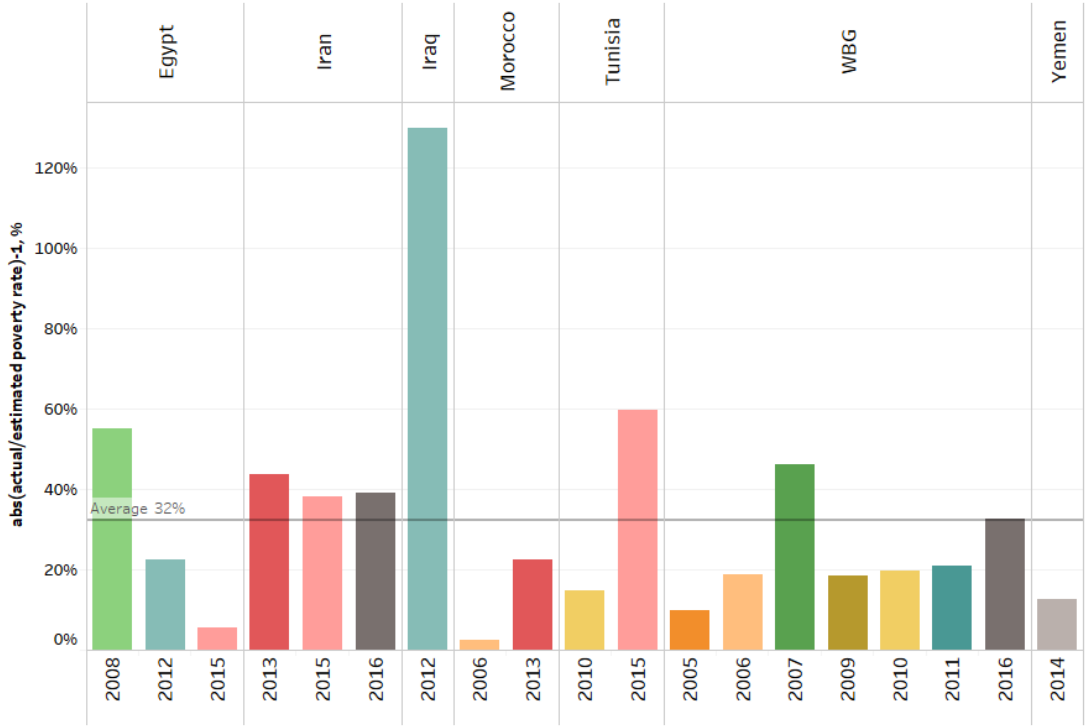

Source: Authors' calculations using MENAPOV data, GDP per capita growth rates are from WDI.
Note: For all countries $3.2 2011 PPP poverty line is used, while for WBG $ 5.5 2011 PPP line is used. WBG stands for West Bank and Gaza.

Estimation errors stem from problems related to distribution-neutral method assumptions. This method assumes a one-to-one relationship between GDP per capita and household consumption across the whole distribution. This assumption and may not hold for many different reasons. In the Islamic Republic of Iran

and the West Bank and Gaza, for example, the method clearly did not work. In the Islamic Republic of Iran, the government distributed universal cash transfers to compensate for increase in energy prices. This had a strong counter-cyclical effect, compensating for economic labor market slowdown and increasing expenditure for the poorest (World Bank, 2018b). In the West Bank and Gaza, transfers play a very important role for the population; in Gaza, about 75 percent of the population receives social aid. In these circumstances, poverty is very sensitive not only to economic growth, but to any change in aid flows and transfers (Atamanov and Palaniswamy, 2017).

Figure A3. Absolute growth rate between actual and estimated poverty rates in selected MENA countries, %

Source: Authors' calculations using MENAPOV data, GDP per capita growth rates are from WDI.
Note: For all countries $3.2 2011 PPP poverty line is used, while for WBG $ 5.5 2011 PPP line is used.

Figure A4. Comparing actual and predicted international poverty rates

a) Islamic Republic of Iran, 2009 and 2013, $3.2 2011 PPP poverty line	b) West Bank and Gaza, 2011 and 2016, $5.5 2011 PPP poverty line
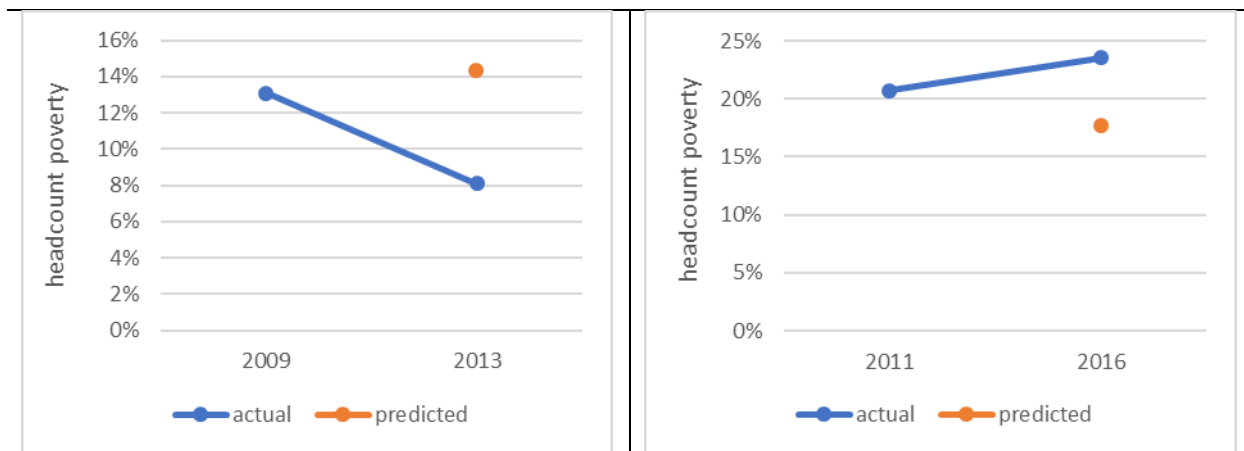
Source: Authors' calculations using MENAPOV data, GDP per capita growth rates are from WDI.

A.2. Using Labor Force Surveys (LFS) to measure monetary poverty

Despite the fact that consumption per capita is the preferred welfare indicator for the World Bank's analysis of global poverty (World Bank 2015), many countries use income as a measure of well-being. Leaving aside the discussion of why using consumption is preferable in developing countries, let us discuss potential issues related to measurement of income by using LFSs.

LFSs are not designed to measure well-being and are focused on capturing accurate labor market indicators primarily related to employment and unemployment. For example, LFSs target the population above age 15, while poverty measures include the whole population. LFSs collect income data, but typically this is detailed information for labor-related income, while other non-labor related income sources—public and private transfers, income from financial assets—can be missing or be less detailed. LFSs typically do not collect information on housing and assets, which may be important to accurately rank population by welfare status.