Obstructed poverty reduction: growth-passthrough analysis

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Obstructed poverty reduction: growth-passthrough analysis

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Key messages

- *Even under full passthrough of national growth to household incomes, poverty reduction during 2019-2030 is projected to be modest and the world is unlikely to eradicate extreme poverty or halve poverty using national poverty lines.*

- *This projected outcome is linked in part to the impact of COVID-19, but the pandemic is not the main factor behind modest poverty reduction.*

- *Developing countries should not only focus on policies that promote GDP growth at the national level but also consider its passthrough rate to household incomes.*

Executive summary

Can the world still reach Sustainable Development Goal (SDG) 1 targets 1.1 and 1.2 by 2030? This question is particularly relevant in light of COVID-19 having derailed many developing economies. Current methods for assessing progress regarding development are limited in that they assume a full transmission of macroeconomic growth forecasts derived from national accounts to household level income captured by surveys. This study offers two contributions. Firstly, a methodology was developed for estimating this passthrough effect using unsupervised clustering methods and results were reported at the regional and country levels. Secondly, it used these passthroughs to discount Personal Consumption Expenditure (PCE) growth forecasts available for 183 countries, which were then applied to estimate headcount poverty rates using the extreme poverty line of $1.9 per day and national poverty lines.

The results showed that in the best-case full growth passthrough scenario, modest poverty reduction was recorded but the world was still unlikely to reach SDG1 targets 1.1 and 1.2 by 2030. With more realistic scenarios, where modelled growth passthrough results were applied, the poverty forecasts showed only a slight dent from their 2019 baseline. The policy implications of these findings are that developing countries, especially poorer countries, should be concerned with macroeconomic policies that enhance PCE growth, as there is not sufficient growth in national income to reach poverty reduction targets. Moreover, these policies should also aim at enhancing passthrough to household incomes. Finally, a weaker growth-poverty nexus gives way to stronger responsiveness to shifts in income inequality. Policies targeting inequality reduction should also be prioritized.

Contents

Introduction

Changes in money metric poverty, commonly measured using the poverty headcount ratio, regardless of the choice of poverty line, can be attributed to two underlying components: a *growth effect*, or change in the level of real income, and a *distributional effect*, a change in the distribution of incomes (Kakwani, 1990; Datt and Ravallion, 1992; Eicher and Garcia-Penalosa, n.d.). A major question in development studies is concerned with the relative importance of growth versus distribution in poverty reduction.

In the 1970s, amid the high postwar growth experienced by many developing countries, some influential studies (Chenery and others, 1974) claimed that economic development experiences either left the poor behind or worsened their situation. In the poorest countries, earlier studies also argued that poverty reduction was hampered by relatively low growth rates combined with increasing inequality (Ahluwalia, Carter and Chenery, 1979). In recent years, evidence suggests the bulk of the poverty reduction observed in developing countries is linked to the growth effect. However, within and between countries, inequality has also led to reductions in poverty – a so-called double-dividend effect (Bourguignon, 2004; Alvaredo and Gasparini, 2015).

Adding more analytical insights, Lakner and others (2020) argued that the poverty impact of more inclusive growth varies across countries and depends on the initial levels of poverty, the distribution and the growth incidence curve. At high levels of initial poverty, inequality reduction could impede poverty reduction in the short term compared with a distribution-neutral growth scenario. Bergstrom (2020) confirmed that a 1 per cent reduction in inequality leads to a larger poverty reduction on average than a 1 per cent increase in mean income. Fosu (2017) showed that the elasticity of poverty to inequality tends to be larger on average than the growth elasticity of poverty (GEP) in absolute value. Other studies concluded that the GEP is negatively related to initial inequality (Ravallion, 1997, 2001; Kraay, 2006).

The continued significance of this debate on the relative importance of growth and distribution factors is clear, especially in light of post-COVID-19 pandemic renewed interest in poverty estimation and reduction policies. For example, Abu-Ismail (2020) confirmed the effect of the COVID-19 pandemic on poverty in 14 non-Gulf Cooperation Council (GCC) countries, where grouped household income and expenditure survey data was used. The pandemic was expected to push an additional 16 million people below poverty lines (using national poverty lines) and an additional 9 million people below extreme poverty lines (using the $1.9 poverty line) in the Arab region in 2021.

In this paper, we show that poverty forecasts are hypersensitive to whether survey-based or national-accounts estimates are used. This should not be surprising given the literature on the subject. Deaton (2005) argued that survey-based estimates of consumption understate mean consumption and overstate the number of individuals in poverty when wealthier households under-comply with the survey compared to poor households. Recent literature suggests that the selected non-compliance may be a problem in both tails of the distribution (Bollinger and others. 2019). Also, in many poorer countries, using consumption growth as measured in household surveys is problematic as it grows at a slower rate than measured in national accounts (Ravallion 2003; Deaton 2005; Prydz and others 2019). However, survey and national accounts results are expected to converge as methods to estimate income from national accounts and surveys improve, as is the case in the richest countries.

Notwithstanding their sources, the magnitude of the difference between survey and national accounts growth has major implications for poverty nowcasting and forecasting results. As surveys are not regularly updated for most countries, some adjustment is needed to allow for continuous poverty monitoring at national, regional or global levels. To align cross-country poverty comparisons to a common reference year, national accounts data remains the best option available to interpolate and extrapolate survey estimates. However, the use of national accounts data to impute survey-based poverty estimates, as applied in several studies, including by the World Bank, entails a major limitation: the assumption of a full passthrough between national accounts growth and survey-based income growth (Ravallion 2003; Deaton 2005; Deaton and Kozel 2005). The inherent biases that tend to overestimate consumption expenditure growth in national accounts for poorer countries may lead to a biased estimation of poverty.

To overcome this limitation, this paper proposes a poverty estimation methodology that adjusts growth in household income or consumption based on a realistic passthrough factor. Approaches for estimating passthrough rates have been advocated since the early 2000s (Sen 2000; Datt, Kozel and Ravallion 2003; Ravallion 2003; Deaton and Kozel 2005; Pinkovskiy and Sala-i-Martin 2016; Lakner and others 2020). Passthrough factors are expected to vary across different contexts, according to geographic region, income level, welfare measure used (income or consumption), time and other circumstances (Lakner and others 2020). Models linking growth in national accounts to growth in mean household income have been augmented using advanced specifications, additional covariates and interaction terms (Chen and Ravallion 2010; Birdsall, Lustig, and Meyer 2014; Corral 2020).

This paper builds on this literature. It presents several options for forecasting passthrough effects and forecasts headcount poverty ratios till 2030 at the global and regional levels using the international extreme poverty line of $1.9 per day as well as national poverty lines (NPLs). To focus the discussion on the impact of passthrough methodology, all results in this paper are based on neutral-growth income distribution in all forecasting scenarios.

The paper is structured as follows: Section 1 reports on stylized facts using the simple ratio of the levels and trends in private consumption expenditure derived from national accounts to trends in incomes or consumption expenditures derived from household budget surveys. Section 2 introduces the methods for estimating future passthrough rates. Section 3 presents the results of our estimated passthroughs. Section 4 reports on poverty headcount projections towards 2030 based on these model estimates and compares them to results based on full passthroughs under the $1.9 per day and NPLs.

1. Growth passthroughs: stylized facts

In most developing countries, only a portion of the growth in national accounts passes through to the mean household income/consumption expenditure per capita captured by surveys (Ravallion 2003). Four key reasons for this disparity are identified in the literature:

1. National accounts and survey data are collected differently and at different levels. Household surveys are designed to measure income and consumption expenditure at the household level; components of income and consumption expenditure are self-reported through personal interviews and compiled by enumerators. By contrast, private consumption expenditure in national accounts is often imputed as the residual after subtracting other (measured) forms of domestic absorption from aggregate output (Ravallion 2003).
2. Mean income/consumption expenditure in surveys is typically underestimated due to systematic underreporting and unit and item nonresponse.
3. Sudden economic shocks are sometimes not captured in the growth of survey-based mean income/consumption expenditure.
4. Survey sampling is not representative and errors occur in sample frames and survey measurement.

This section of the present report focuses on the historical cross-country stylized facts regarding the scale of the passthrough effect. To estimate this, we analysed growth spells for 183 countries. Given that countries do not have the same number of observations, the sample was restricted to only the most recent $\boldsymbol{S}$ survey years per country. This was in order to obtain a near balanced-panel sample, without sacrificing sample size. In our analysis, $\boldsymbol{S}$ was selected using the median count of occurrences across countries, which is 3 ($\mathbf{2} \leq \boldsymbol{S_i} \leq \mathbf{3}$ for all countries i, to observe one or two periods of growth).

We analysed growth in survey-based mean income/consumption expenditure between consecutive survey years for 183 countries. Successive survey years were used to construct each growth spell, with up to two growth spells T per country, T_{latest} for all countries, and T_{ealier} for countries with $S_i = 3$ (refer to annex 1 for more information on the country year observations dataset).

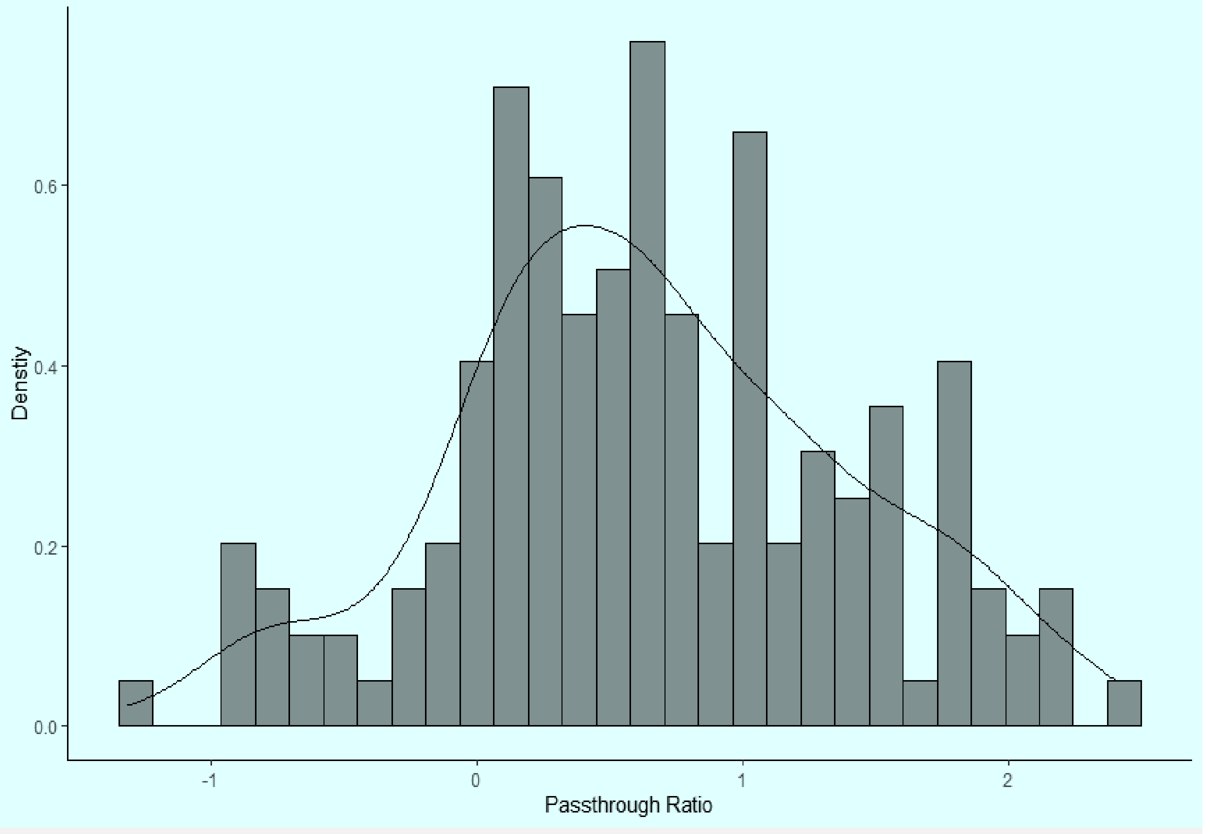
The growth spells ranged from 1 to 17 years between 1992 and 2019 for T_{latest}, and 1 to 18 years spanning between 1990 and 2018 for $T_{earliest}$ (refer to table A1.1 in the annex).

We computed the simple passthrough ratios for the $T_{earliest}$ and T_{latest} periods as follows:

Figure 1 shows that country level passthroughs were dispersed around the worldwide mean of 0.649 (0.629 population weighted) with a standard deviation of 0.75. Passthrough ratios differed from region to region (figure 2). For developing and low-income regions, the ratios tended to be lower, regardless which time spell was used. While other world regions scored between 0.8 and 1.2, the Arab region and Sub-Saharan Africa scored below 0.4. These two regions share common characteristics, including medium-to-high poverty headcount ratios, low-to-medium poverty lines and mean/median incomes, and high-income inequality.

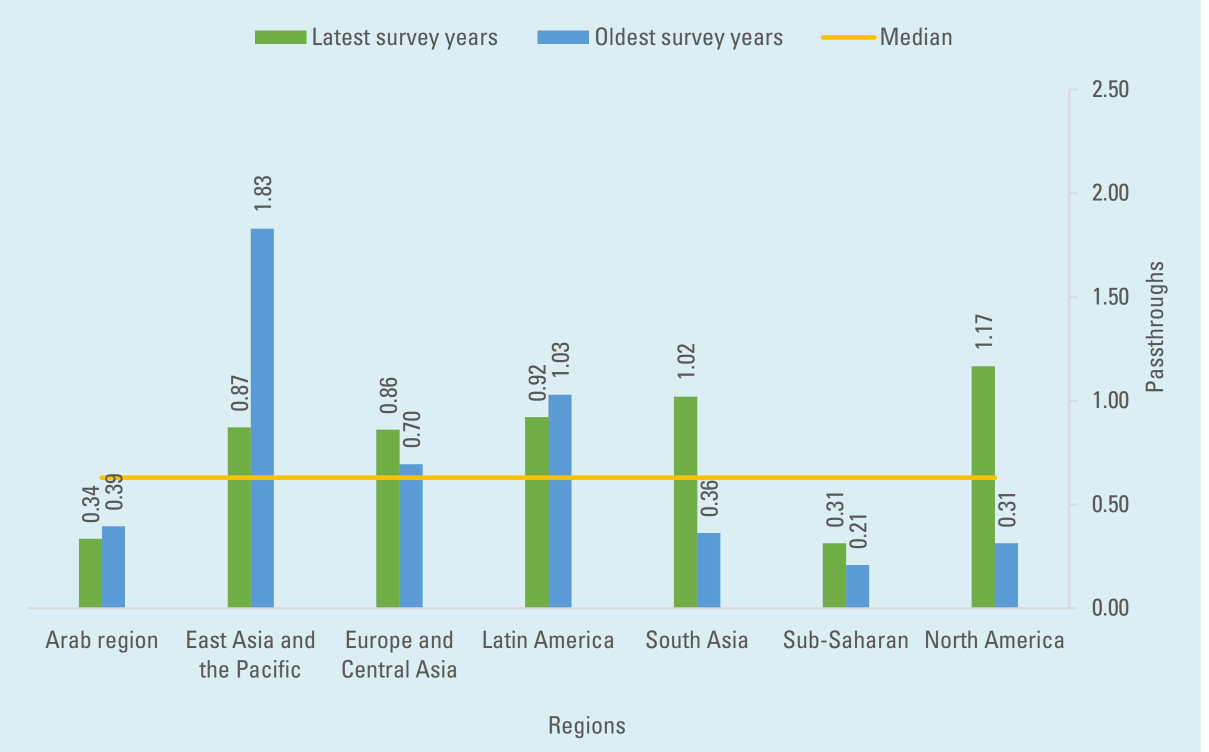
$$Country's\ passthrough = \frac{\%\ annualized\ growth\ in\ survey - based\ mean\ income\ over\ a\ spell}{\%\ annualized\ growth\ in\ PCE\ over\ the\ same\ spell} \tag{1}$$

Figure 1. Country level passthrough ratios for the latest spell T_{latest}



Source: Authors' calculations.
Note: 183 countries were evaluated. Only 167 countries fit the criteria of having two recent successive surveys for which the passthroughs can be computed; 17 per cent of those values are not represented in the figure 1 histogram (cut-off below -1.5 and above 2.5) (the distribution of the passthrough outliers by world regions is presented in figure A1.1 in the annex). Smooth line refers to the kernel density function.

Figure 2. Observed passthroughs across world regions (Country population weighted)

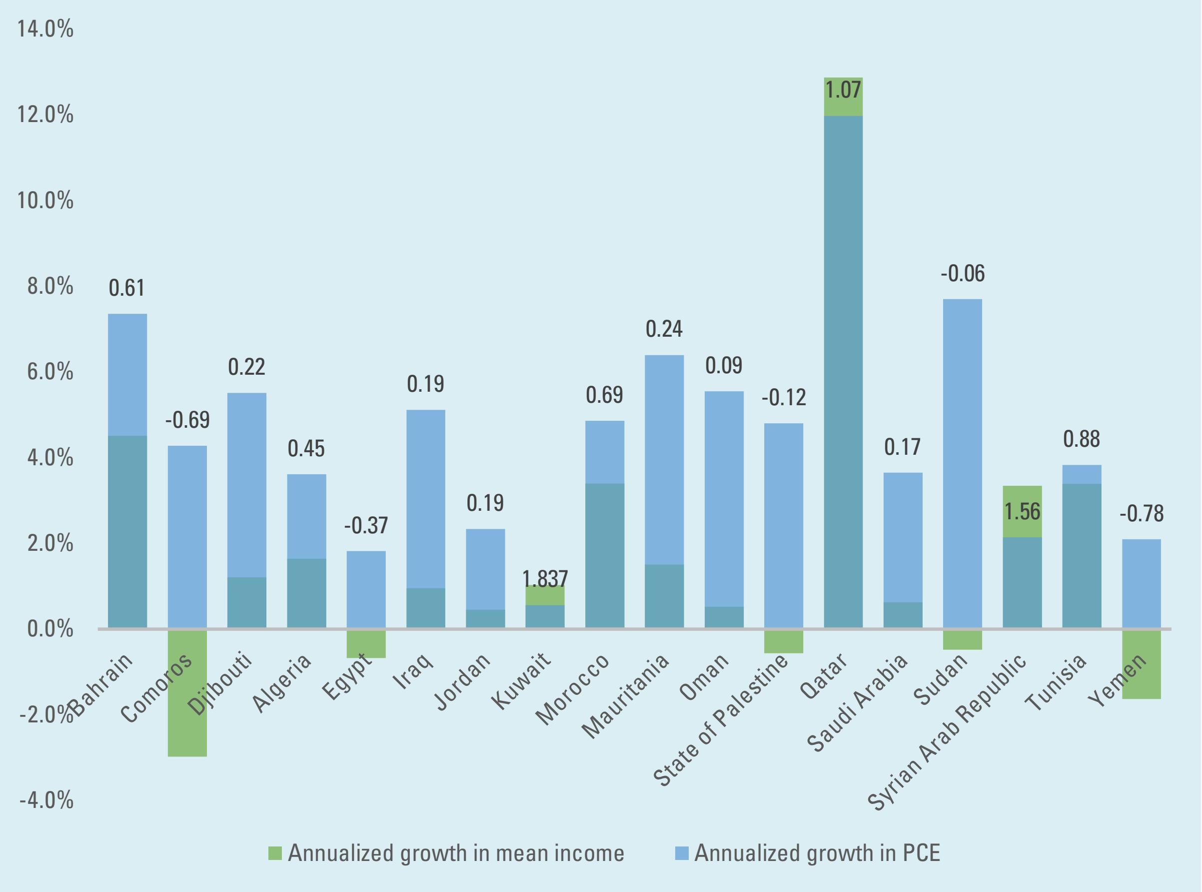


Source: Authors' calculations.
Note: The orange line is the global passthrough average of 0.629 for the latest spell.

While the latest and earlier spells exhibited similar passthrough ratios for most regions, East Asia and the Pacific, South Asia and North America showed significant changes. The reason is that each of these regions includes countries with high population concentration. Slight changes in personal consumption expenditure (PCE) growth or in survey mean income growth from one spell to another for countries like China, India, Indonesia or the United States may lead to a significant change in their respective regional average. In fact, the 1.83 population-weighted regional passthrough rate for East Asia using the latest spell was caused by an observed passthrough value of 10 for Indonesia, associated with a large percentage growth in mean income and a reported small percentage growth in PCE. Similarly, India's passthrough changed from 0.22 to 1 from one spell to another, causing an increase in South Asia's population weighted regional passthrough rate. Similarly, North America's estimated passthrough rate was computed using only two countries (Canada and the United States) and also exhibited a large change between the spells.

The low passthrough rate for the Arab region is particularly interesting given that its income per capita levels should place it at a significantly higher level than observed. The low passthrough rate was evident even for high-income countries such as Saudi Arabia and Oman. However, the Syrian Arab Republic (pre-conflict), Kuwait, Morocco, Qatar and Tunisia recorded the highest passthrough rates compared to other countries. The high diversity between country levels shows that there can be no reliable regional narrative for the passthroughs. More consistent results might be revealed from country comparisons based on income levels, as highlighted in the results in section 3.

Figure 3. Annualized growth in survey-based mean income/consumption expenditure and PCE over the latest spell T_{latest}



Source: Authors' calculations.
Note: The values at the top of each bar are the observed passthrough ratio. The passthrough rate for the Syrian Arab Republic was based on old survey years.

2. Forecasting passthroughs: data and methodology

A. Data sources

The main data used to project poverty headcount rates were compiled from the World Bank's PovcalNet and the Global Monitoring Database of the recent household income and expenditure surveys extracted from national sources. The primary data included: poverty headcount (per cent); poverty line (purchasing power parity (PPP)$/day and/month); mean (PPP$/month), median (PPP$/month); Gini index; population; population density (people per sq. km of land area); urban population share (per cent); and age dependency share (per cent), as well as categorical variables for the welfare aggregate (consumption or income), poverty lines (absolute or relative) and country income group (high, upper-middle, lower-middle and low income). For countries for which data were not available on PovcalNet,[1] we relied on other data sources such as reports published by national statistical authorities and national reports. We estimated poverty measures for 183 countries belonging to 7 world regions according to the United Nations regional classifications. Summary statistics for the overall sample and for each world region are shown in tables A1.1, A1.2 and A1.3.

Using the latest household surveys available for each country, we nowcasted to our baseline year, 2019, and then projected poverty for the years 2020-2030 using national accounts growth forecasts provided by the United Nations Department of Economic and Social Affairs (DESA) based on the World Economic Forecasting Model (WEFM).[2] We relied on the PCE projections as the preferred national account option (also referred to as household final consumption expenditure (HFCE)) from the April 2021 edition of the WEFM, which accounts for the impact of COVID-19 on economic activity. PCE measures consumer spending on all goods and services, including durable goods, rent (but not household purchases of dwellings) and non-governmental organizations' spending on households.

1 Countries not available on PovcalNet notably include: Afghanistan, Bahamas, Bahrain, Barbados, Brunei Darussalam, Cambodia, Hong Kong, Kuwait, New Zealand, Oman, Qatar and Saudi Arabia.

2 Growth rates in PCE between the base year and the target year were retrieved from the WEFM developed DESA to produce consistent forecasts for the global economy. For more on the models developed, please refer to Altshuler, Clive; Holland, Dawn; Hong, Pingfan; Li (2016). The model applies a cointegration/error correction framework (Johansen 1988) and relies on a simplified context in which long-run relationships are specified in line with standard macroeconomic theory and core behavioural relationships are specified as error-correction processes.

B. Methodology

There are several established methods for computing the relationship between growth rates in surveys and those in national accounts:

- Simple ratios.
- Regression (simple or multiple regression).
- Clustering the countries into subgroups (not necessarily geographically) and finding the relevant passthrough for each subgroup.

Once the passthrough factors were estimated, we used them to project survey-based mean income/consumption expenditure nowcasted to the base year:

As mentioned earlier, we used PCE growth projections obtained from the WEFM rather than GDP growth projections since PCE is a fraction of GDP that is highly relevant to the economic activities captured by household surveys (Prydz and others 2019).

For the empirical exercise, countries with missing survey or national accounts data were excluded. Statistical outliers outside of the interquartile range for the computed passthroughs were also removed. This left a smaller dataset of 167 countries and 294 growth spells for the years 1990 to 2018. For each spell, the annualized growth in private consumption expenditure in national accounts and the survey-based mean income/consumption expenditure were computed.

1. Simple ratios

Having estimated the passthrough factors as simple ratios as in $Equation\ (1)$, some of the computed passthrough factors had negative signs. For such cases, the negative values were replaced by the minimum non-negative country ratio in its respective geographic region.
For countries with extremely high ratios, exceeding unity, their values were replaced by 1. The regional and global corrected averages were then computed (population-weighted aggregations).

2. Regression analysis

To avoid the issue of the presence of outliers, a simple linear regression model was used, where the annualized growth in the survey-based mean income/consumption expenditure was regressed against the annualized growth in PCE in national accounts as in $Equation\ (3)$ (Ravallion 2003; Lakner and others 2020).

Country-level subscripts i were omitted for simplicity. We assessed whether there were systematic or structural differences across regions. We applied the same regression separately for each of seven world regions j according to the United Nations geographical classifications. As an alternative model that was more robust to small sample sizes for some regions, we also regressed the ratio of survey-based mean income/consumption expenditure to PCE on regional dummy variables (see $Equation\ (4)$).

This model could be augmented by including more variables. Since for some countries, more frequent surveys were available, and to make use of all the sample data at hand (i.e., not only relying on the latest surveys), pooled data regressions were also applied and the results are reported in table 1 (refer to annex 1 for more on the country year observations dataset).

$$Mean\ income_{projected} = Mean\ income_{baseyear} * [1 + (PCE\ growth\ rate\ * Passthrough\ factor)]$$	(2)
$$g_{mean\ income} = \beta_0 + \beta_1 * g_{PCE\ per\ capita} + \epsilon$$	(3)
$$\frac{\%\ growth\ in\ survey - based\ mean\ income\ over\ a\ spell}{annualized\ \%\ growth\ in\ PCE\ over\ the\ same\ spell} = \sum\beta * Region\ Dummy\ + \epsilon$$	(4)

3. Clustering methods

(a) Partitioning around medoids

Beside regression-based methods, machine learning algorithms were applied for clustering country observations and using cluster results for projecting household survey-based mean income/consumption expenditure based on PCE projections. This was useful for determining how the passthrough rates varied across different contexts.

This method entailed clustering data using an unsupervised machine learning technique, the partitioning around median values or medoids (PAM). This was used to better read the data, understand natural divisions and subgroups in the data, and assign passthroughs that were in some aspects representative of the relevant subgroups. The aim of clustering was to minimize the distance between observations in a certain subgroup around a specific observation and maximize the distance between clusters. The method relied on regressing the annualized growth in PCE over the annualized growth in survey-based mean income/consumption expenditure (as in $Equation\ (3)$) for the clustered observations subgroup. This was done for all subgroups. In $Equation\ (3)$, the subgroups were delineated by geographic regions, while here they were defined by economic proximity among observations.

This technique involved identifying the number of clusters to partition the data into, where multiple metrics were available to select the optimal number. One option involved performing a silhouette analysis utilizing an internal validation metric, which highlighted how similar an observation was to its own cluster compared to its closest neighbouring clusters. The metric ranged from -1 to 1, with higher values being preferred as they facilitated splitting data into subgroups more efficiently. The silhouette analysis of our data showed that the data could be efficiently grouped into seven or more clusters (figure A1.2). As the number of clusters increased, the silhouette width also increased – the clustered observations in any subgroup were distant from the observations in other subgroups. However, the higher the number of clusters, the lower the number of observations in each cluster, leading to biased or overfitted results for each subgroup. The silhouette method can be interpreted as a post-estimation, but as with any machine learning method, the count of clusters serves as a hyperparameter which can be tuned in an iterative way.

Because of the variety of variables used, including numerical and categorical variables,

Gower distance (rather than Euclidean distance) was employed to compute the distance between two or more observations. Gower distance is a metric that measures the dissimilarity between two observations with mixed types (categorical or numerical). For numerical data, Gower distance is the absolute value of the difference, normalized by the range of the variable.
For binary variables, the distance between observations is 0 or 1. The total distance between two country observations is the average of the distances of all variables defining the two observations.

When selecting the distance criteria and the number of clusters k, the algorithm assigned every observation to a cluster represented by its centre, centroid. The centre minimizes the dissimilarity of observations to other points in the cluster. Conventional clustering methods rely on the k-means approach, whereby the centroid is placed at the mean of cluster observations. Since our data contained some extreme values, and included both numerical and categorical variables, a k-medoid approach was implemented instead, based on the cluster's median – itself part of the data of each cluster. The procedure was: randomly selecting candidates for a medoid in each cluster and assigning all observations to their closest medoid using Gower distance. Across all candidate medoids, identify the observation that would yield the lowest average distance to other cluster observations where it was assigned as the medoid. Finally, we ran a regression using ($Equation\ (1)$) in each cluster using that selected medoid and computed the passthrough factors.

Each cluster was investigated separately by performing descriptive analysis over both categorical and numerical variables: region; welfare measure (consumption or income); poverty headcount ratio; poverty line; median and mean values of income/consumption expenditure; and Gini index. To test the performance and robustness of the machine learning method and check how sensitive the results were to different subsets of the data, cross-validation was undertaken (refer to annex 2 for a thorough demonstration).

(b) Model based recursive partitioning

In many situations, it is not reasonable to assume that a single global model can fit all observations. However, it might be possible to partition observations in respect of other covariates. Therefore, this clustering technique relied on partitioning data and estimating regression coefficients β_1 for subsets/partitions of data ($Equation\ (3)$). To assess whether partitioning data was necessary or not, a fluctuation test was performed for assessing the instability of the parameters. If any instability under a significant level (5 per cent in our case) was detected with respect to any of the covariates, the daughter nodes were split in two.

This model based (MOB) recursive partitioning method was attractive as it made it easy to visualize the grouping of data. It evaluated whether the passthrough factor (represented by the coefficient β_1) differed across different subgroups using a statistical test based on a chosen *p-value* (Lakner and others 2020); thus, it was based on well-established statistical models.

The algorithm functioned as follows:

1. Fit a global model to all observations ($Equation\ (3)$) and estimate β_1.
2. Assess the parameter stability with respect to every covariate (poverty line, Gini index, population, region, etc.). Fluctuation tests

(depending on the type of variables, categorical or numerical) were used to assess the stability of each covariate (the test corresponded to the null hypothesis that evaluated the stability). For more on the tests, please refer to Zeileis and Hornik (2007). The test returned *p-values* results for every variable.

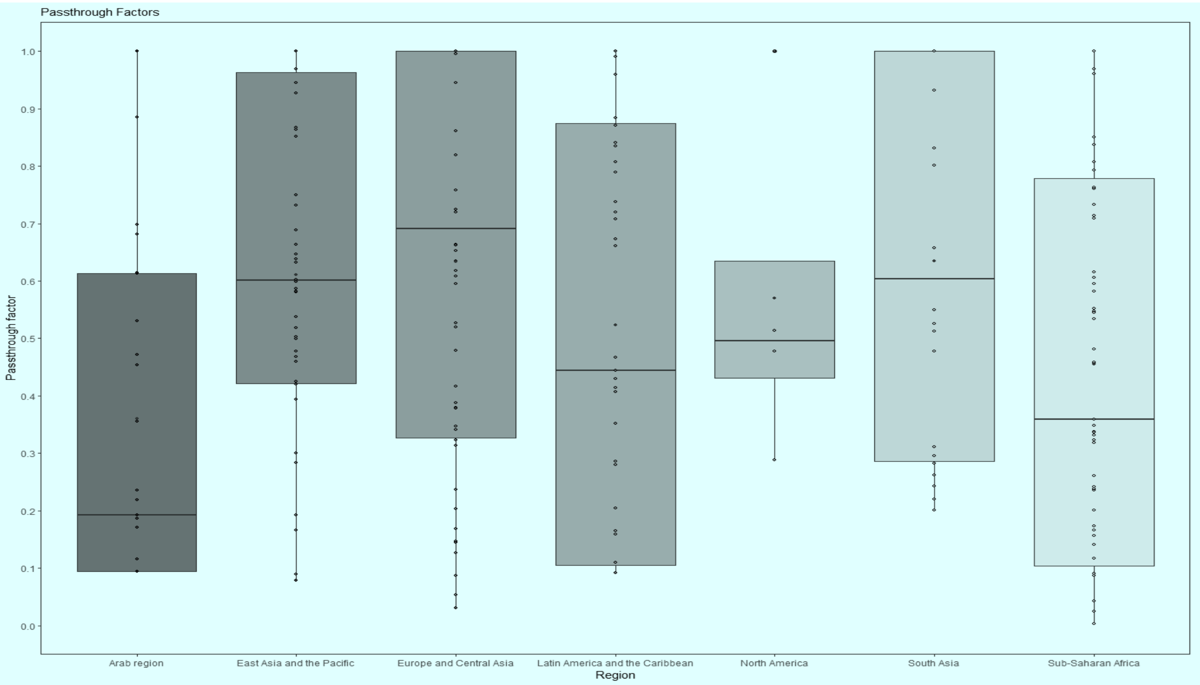
3. Select the variable associated with the highest instability (lowest *p-value*) and proceed to the splitting stage.
4. Compute the cut-off (or split point) for the chosen variable. The cut-off optimized the parameter estimation β_1 under the maximum likelihood approach. The data was then split into two daughter nodes.
5. Steps 2 to 4 were repeated and the algorithm stopped as soon as the stability condition was met. Not all variables had to be subjected to a split. The only additional hyper-parameter (other than the p-value) used for calibration was related to the minimum number of observations per node (this was imposed to avoid the problem mentioned in the PAM model and ensured sufficient observations in a cluster). In our analysis, the minimum observations per node was set at 20 observations.

3. Results – Regional and other subgroup level passthroughs

Using the simple ratios approach, the global passthrough factor was estimated at 0.62 (country population weighted). At the regional level, the East Asia and the Pacific region exhibited the highest rate with 0.73, followed by Europe and Central Asia with 0.60 (table 1). The lowest passthrough factor was recorded in the Arab region at 0.26, followed by 0.39 in Sub-Saharan Africa.

Figure 4 illustrates a boxplot of the passthrough results using the simple ratio approach, distributed among geographic regions. All regions exhibited a large degree of dispersion in that their inter-quartile ranges were wide and there were outliers outside of those ranges. The elongated upper whiskers (outside the middle 50 per cent of observations) in the Arab region, Latin America and the Caribbean, and Sub-Saharan Africa indicate that country passthroughs varied substantially amongst the upper quartile group of member countries. By contrast, this was not the case in regions with higher typical passthroughs.

Figure 4. Boxplot for regional passthroughs estimated using the simple ratio model



Source: Authors' calculations.

Regions such as East Asia and the Pacific, Europe and Central Asia, and South Asia had distributions more skewed to the right with noticeably lower whiskers. The choice of data had an impact on these findings. The annualized growth rates and consequently the passthrough rates were governed by the choice of the survey years. For example, Thailand's passthrough changed from 0.079 to 1.000 when changing the spell period from earliest to latest.

Table 1. Passthrough factors[a] for different models, aggregated by region

Model	Region							
	Arab region	East Asia and the Pacific	Europe and Central Asia	Latin America and the Caribbean	North America	South Asia	Sub-Saharan Africa	Worldwide (population weighted)
Simple ratio	0.258	0.733	0.603	0.612	0.595	0.562	0.388	0.620
Regression model – region specific[b,c]	0.323 (0.096)	0.694 (0.062)	0.785 (0.057)	0.607 (0.11)	0.608 (0.221)	0.465 (0.117)	0.343 (0.063)	0.558 (0.033)
Regression model – Region specific[e]	0.319 (0.106)	0.704 (0.081)	0.736 (0.075)	0.597 (0.14)	0.813 (0.258)	0.466 (0.15)	0.352 (0.066)	0.514 (0.039)
Regression model – region as dummy variable[c,d]	0.257 (0.123)	0.673 (0.087)	0.761 (0.078)	0.519 (0.092)	0.630 (0.312)	0.711 (0.125)	0.454 (0.078)	0.558 (0.033)
Regression model – region as dummy variable[e]	0.238 (0.136)	0.650 (0.108)	0.816 (0.091)	0.516 (0.109)	0.743 (0.385)	0.768 (0.153)	0.471 (0.085)	0.514 (0.039)
Clustering based on distance PAM – region added	0.493	0.779	0.757	0.596	0.791	0.366	0.314	0.611
Clustering based on statistical testing MOB	0.183	0.760	0.764	0.605	0.752	0.442	0.343	0.645
Clustering based on distance PAM – (without region)	0.450	0.780	0.694	0.617	0.704	0.581	0.341	0.686

Source: Authors' calculations.
Notes: Regional results were obtained after accounting for country population weights.

- [a] Standard errors in parenthesis.
- [b] Adjusted R-squared for all the regional models are 0.264, 0.696, 0.738, 0.381, 0.621, 0.361, and 0.297, respectively.
- [c] Restricted survey years sample.
- [d] Adjusted R-squared is 0.457.
- [e] Pooled data.

The coefficient β_1 from $Equation\ (3)$ could also be used for the fraction of growth in PCE per capita that was passed through to survey-based mean income/consumption expenditure. Estimated on 294-time spells, this yielded a global value of $\widehat{\beta_1} = 0.558$. β_1 equal to unity would have implied that growth in PCE was unbiased for growth in survey-based mean income/consumption expenditure, but this was clearly rejected. The passthrough rate estimated using the regression method was similar to that estimated using the simple ratio method. The intercept was estimated at zero ($p \geq 0.05$). Estimating the regression at the regional level, the results were also similar to those using the simple ratio method. Table 1 summarizes the passthrough results across the alternative models.

Different regions had different fractions. Countries in the same region were assigned the same regional passthrough coefficient, which was clearly restrictive for some countries. However, the results obtained so far showed that regardless of the model used, the Arab region and Sub-Saharan Africa had the lowest passthrough ratios. On the other hand, with regions where the concentration of developed countries was higher, fractions tended to be higher.

Table 2. PAM clustering according to Gower distance summary (Region included)

Cluster	Passthrough β	Regions	Welfare measurement	Population (millions)	Headcount ratio *(percentage)*	Poverty line ($/day)	Median income/ consumption expenditure	Mean income/ consumption expenditure	Gini index *(percentage)*
I	0.482 (0.122)	South Asia	Consumption	110	26.67	3.1	139.82	120	34.85
II	0.343 (0.63)	Sub-Saharan Africa	Consumption	15	43.08	2.29	83.19	90	44.08
III	0.742 (0.78)	Europe and Central Asia	Consumption	9	20.59	5.6	393.5	300	31.91
IV	0.632 (0.11)	Latin America and the Caribbean	Income	10	30.38	6.7	276.3	400	47.08
V	0.866 (0.09)	Europe and Central Asia	Income	10	13.08	20.7	1242.1	1500	33.19
VI	0.706 (0.07)	East Asia and the Pacific	Consumption	94	17.77	2.5	170.05	200	36.41
VII	0.174 (0.082)	Arab region	Consumption	17	21.1	3.3	144.5	180	35.18

Source: Authors' calculations.
Note: The covariate values under each cluster represent the medians of each cluster.

Moving into the clustering methods, and starting with the PAM method, the regional and global results are listed in table 1. The choice of variables used for clustering affected the estimated distance values; the whole clustering process started from the number of clusters and ended with the characterization of each cluster. Since the Gower distance uses the extreme values of 0 or 1 for categorical variables such as regional and welfare-measure indicators (0 for the same region/welfare measure, 1 for different region/welfare measure), categorical variables played an outsized role in data clustering (table 2).

The seven identified clusters are demarcated exactly by geographic region. We therefore intentionally removed the regional variables and observed how clustering performed without the explicit consideration of the region. Five clusters were recommended, compared to seven previously, and four of the five clusters included countries from multiple world regions.[3] The effect of the region was thus absorbed; it no longer overshadowed the effect of the other variables. Table 3 presents the cluster subgrouping results.

Table 3. PAM clustering according to Gower distance

Cluster	Pass through	Welfare measure	Population (mil.)	Headcount ratio *(percentage)*	Poverty line ($/day)	Median income/ consumption expenditure	Mean income/ consumption expenditure	Gini index *(percentage)*
I	0.304 (0.040)	Consumption	20	40	2.16	75	100	42
II	0.675 (0.032)	Consumption	21	15	3.83	187	240	32
III	0.629 (0.052)	Income	15	23	6.9	330	450	45
IV	0.651 (0.07)	Income	63	13	23	1 400	1 700	33
V	0.789 (0.04)	Income	600	11.2	2.3	180	200	35

Source: Authors' calculations.
Note: The covariate values under each cluster represent the medians of each cluster.

3 Cluster I: Sub-Saharan Africa, South Asia, East Asia and the Pacific, Europe and Central Asia, Arab region; Cluster II: Europe and Central Asia, East Asia and the Pacific, Arab region, South Asia, Sub-Saharan Africa; Cluster III: Latin America and the Caribbean; Cluster IV: Europe and Central Asia, East Asia and the Pacific, North America; Cluster V: China and India.

The intensity of the colours inside the table varies with the cluster categories. The lowest intensity-coloured clusters refer to countries with Headcount < 20, poverty line > 15, Median income > 300, Mean income > 450, Gini < 35. The medium intensity-coloured clusters refer to countries with Headcount between 20-35, poverty line 5-15, Median income 100-300, Mean income 150-450, Gini 35-40. The highest intensity-coloured clusters are for countries with values exceeding all of the covariates' cut-offs previously defined.

These results indicate that passthrough rates varied not only across geographic regions, but across other demographic and economic divides. Countries with high poverty headcount ratios tended to have low passthroughs (Cluster I). Poverty headcount was the main factor in the process of clustering data. Unfortunately, the PAM clustering method does not measure the extent and exact effect; rather it yields a contrary path: the lower the poverty headcount, the lower the estimated passthrough rate.

Other variables also played a role in defining the clusters. For instance, low poverty headcount combined with high poverty lines, low Gini index of inequality, and high median or mean income/consumption expenditure are all associated with high passthrough rates (Cluster IV). Population size also had a great effect and, coupled with low poverty headcounts, yielded high passthrough rates such as in China and India (Cluster V). Cluster III was characterized by moderate poverty headcounts and high Gini indices, leading to a middling value for the passthrough rate. Although the median and mean incomes were low in Cluster II, the low poverty headcount and low Gini index gave rise to a high passthrough rate.

For the MOB clustering methodology, the same variables were used as under the PAM classification. With the minimum split per node of 20 observations, we were only able to generate two nodes. The median was selected as the most important factor when it came to splitting the data.

The two fractions obtained were 0.3151 for countries with median income/consumption expenditure less than $146.713/month, and 0.7613 for other countries. Poorer countries, those with lower median income/consumption expenditure or higher poverty headcounts, tended to have lower passthroughs. Next, we expanded our data to all combinations of survey years. Instead of taking successive survey years to form one spell, every possible combination of survey year observations per country was used as a spell. For instance, a country with three survey years was translated into $C_3^2 = 3$ spells. Our data set was thus expanded to encompass 512 time-spell observations. Figures A1.3 and A1.4 show the dendrogram for the clustering process in this exercise. The results included the passthrough coefficients and the standard errors.

When the number of observations increased, both clustering approaches might converge to a single conclusion: high poverty headcount and low median income/consumption expenditure countries recorded low passthrough rates (similar to PAM Cluster I), while high poverty headcount and high median income/consumption expenditure countries were assigned higher passthrough rates. The regression coefficient on median income was highly significant, confirming the systematic differences in passthrough rates between low-median and high-median countries.

For countries with a low poverty headcount ratio, the Gini index and population size separated observations into two subgroups. For high-Gini and highly populated countries, PAM Cluster V is spotted. For lower Gini values, region specific clusters are also spotted and the values/observations previously grouped in Clusters II and IV were then redistributed by region using the MOB method. Both methods resulted in high passthrough rates for these subgroups.

For different choices of hyperparameters and datasets, different decision trees and passthrough estimates were generated. Overall, this clustering method appeared to be transparent but sensitive to the values of all predictive factors and, as a result, its fit might not have been optimal. The annex reports on selected sensitivity and robustness tests.

At the global level, passthroughs in the range [0.55, 0.69] were estimated. The simple ratios and multiple regression methods gave similar results. The simple ratios were computed after removing outliers, while the regression was applied to data with outliers. Removing outliers did not affect the results unduly, either at the global or regional levels.

Regardless of which estimation method was used, the Arab region recorded a low passthrough rate compared to other regions, followed by Sub-Saharan Africa. Europe and Central Asia, and East Asia and the Pacific scored higher rates. South Asia yielded a high passthrough rate in the regression model (where region was introduced as a dummy variable), higher than in the region-specific regression models. The country estimates, just as the regional estimates discussed previously, were very sensitive to the sample survey years and may require careful checks by practitioners. The unsupervised machine learning methods can facilitate efficient and objective estimations.

With regards to the clustering methods, the heterogeneity of the estimated passthrough rates was not governed by geographic regions per se, but by economic factors. Countries with high poverty headcounts, low median income/consumption expenditure and high Gini index recorded low passthrough rates that sometimes fell below 0.3. However, having a high poverty headcount ratio did not guarantee a lower rate. High poverty headcounts combined with medium-level median income/consumption expenditure yielded higher passthrough rates. Machine learning techniques/algorithms contributed by identifying such complex relationships in the presence of nonlinearities.

Countries with low headcount ratios and low Gini indices also yielded high passthrough rates. Other variables contributed to the differentiation of country subgroups, such as region and population size. For instance, high population countries tended to have higher fractions, even if they had low poverty rates and relatively low mean and median income/consumption expenditure levels.

The results of the MOB clustering technique were sensitive to the number of observations in each node and the type of data. The results of the PAM clustering technique were sensitive to the choices regarding the number of clusters, the distance computation method (Gower or Euclidean) and the centroid concept (k-means or medoids). Having a vast number of observations certainly lowered the sensitivity of the results to changes in such hyperparameters. Cross-validation suggested that our results were robust and generalizable at the regional level.

Our key findings demonstrated that developed countries with low poverty rates had high passthrough rates, meaning that a large portion of the growth in national accounts in such countries was passed through to household income/consumption expenditure, as reflected in surveys. For developing countries, the higher the poverty headcount, the lower this fraction was. Passthrough rates did not appear to be clustered by geographic region per se, but by economic and demographic divides, forming distinct subgroups. This did not mean that regional clustering was inappropriate, but it became pivotal at deeper layers, following the differentiation of countries by their poverty headcounts and Gini indices. Other factors such as population density also became relevant at the deeper level of clustering. Ultimately, none of the considered factors solely determined a country’s passthrough rate, but its complex interactions as sieved out by the clustering methods helped to explain it.

4. Prospects for poverty reduction

A. Poverty forecasts: three passthrough scenarios

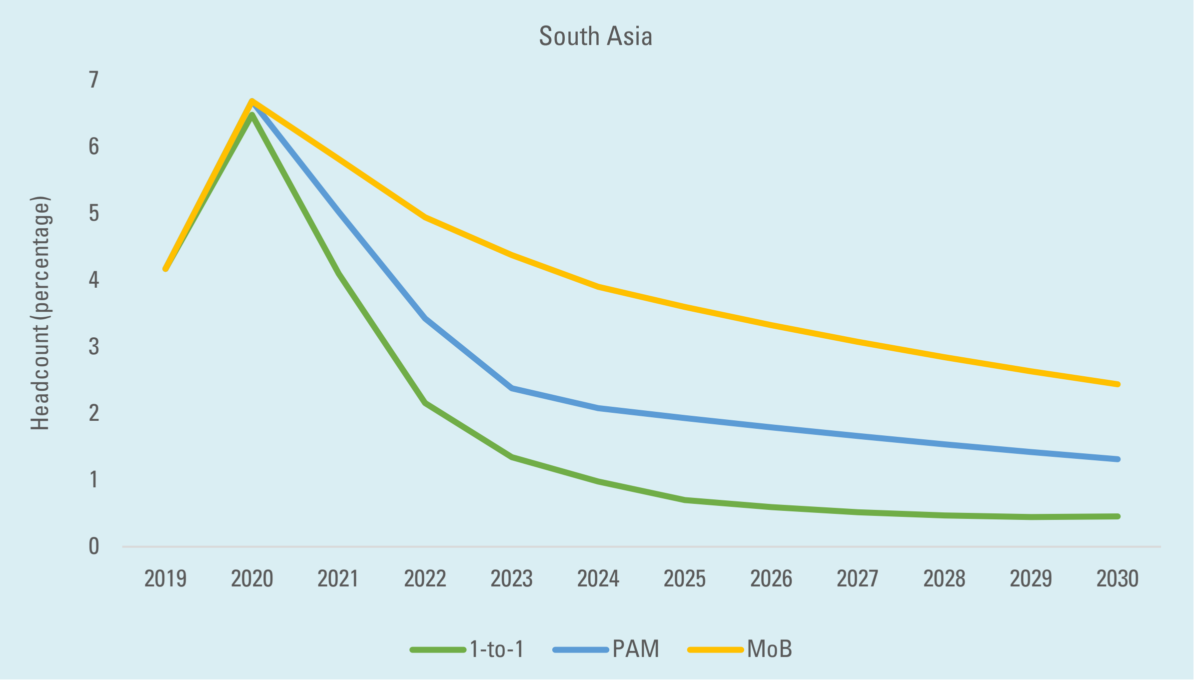
To project the headcount poverty measure ahead towards 2030 at the global and regional levels, we relied on the following assumptions: (a) latest observed national poverty lines (in PPP terms) would continue to apply; (b) constant Gini coefficient – distribution-neutral growth; and (c) PCE growth being dictated by current projections in WEFM.

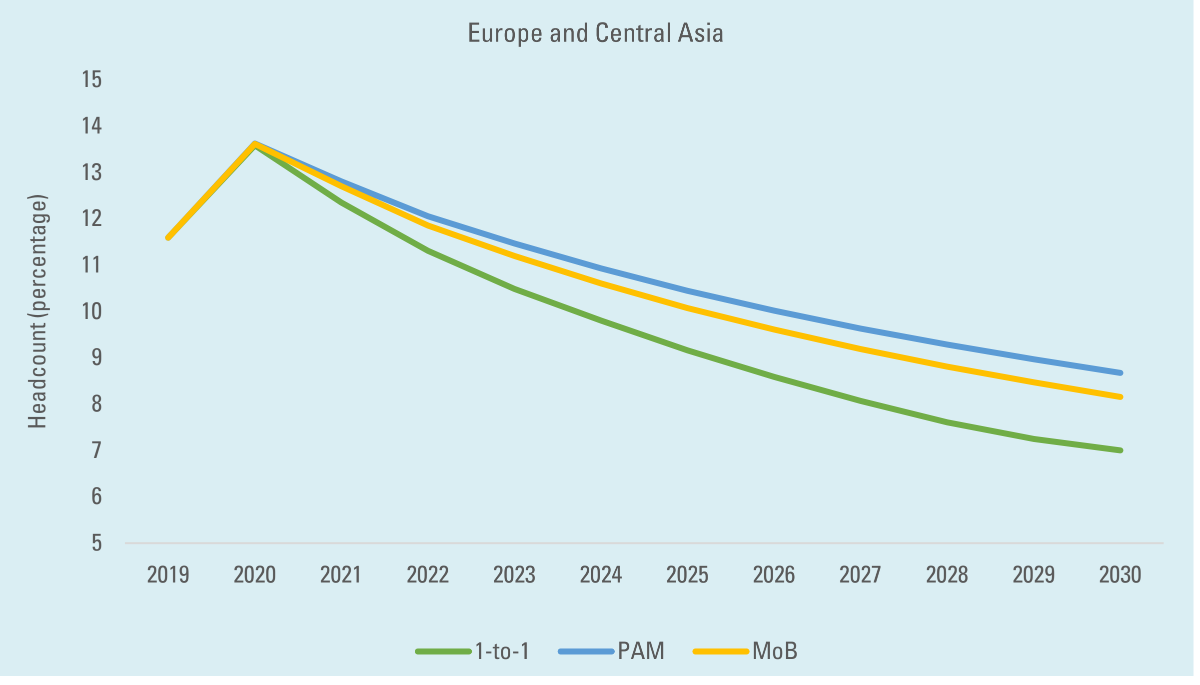
Three poverty trends were calculated for all countries for the years 2020-2030: (a) using full passthrough (PCE growth in national accounts growth was fully reflected in the income/consumption expenditure in household surveys); (b) using passthrough calculated by the MOB cluster technique; and (c) using passthrough calculated by the PAM cluster technique (as in $Equation\ (2)$).

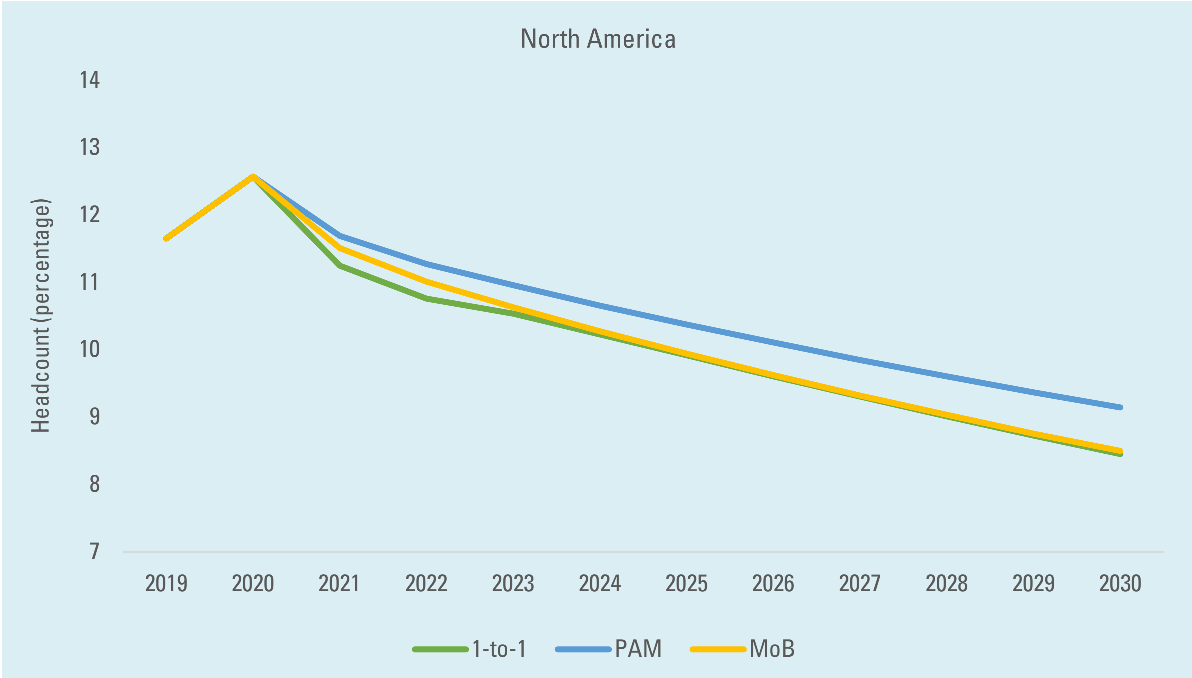
Regional poverty trends (country-population weighted) are presented in figure 5 and figure 6. As expected, the estimates of the year-2019 headcount poverty rates for all world regions were lowest when using the full passthrough specification. Consistent with the recent literature by ESCWA and the World Bank, the headcount poverty ratios increased for all regions in 2020 regardless of the model used, due to the negative PCE growth projections under the pandemic and related economic shocks.

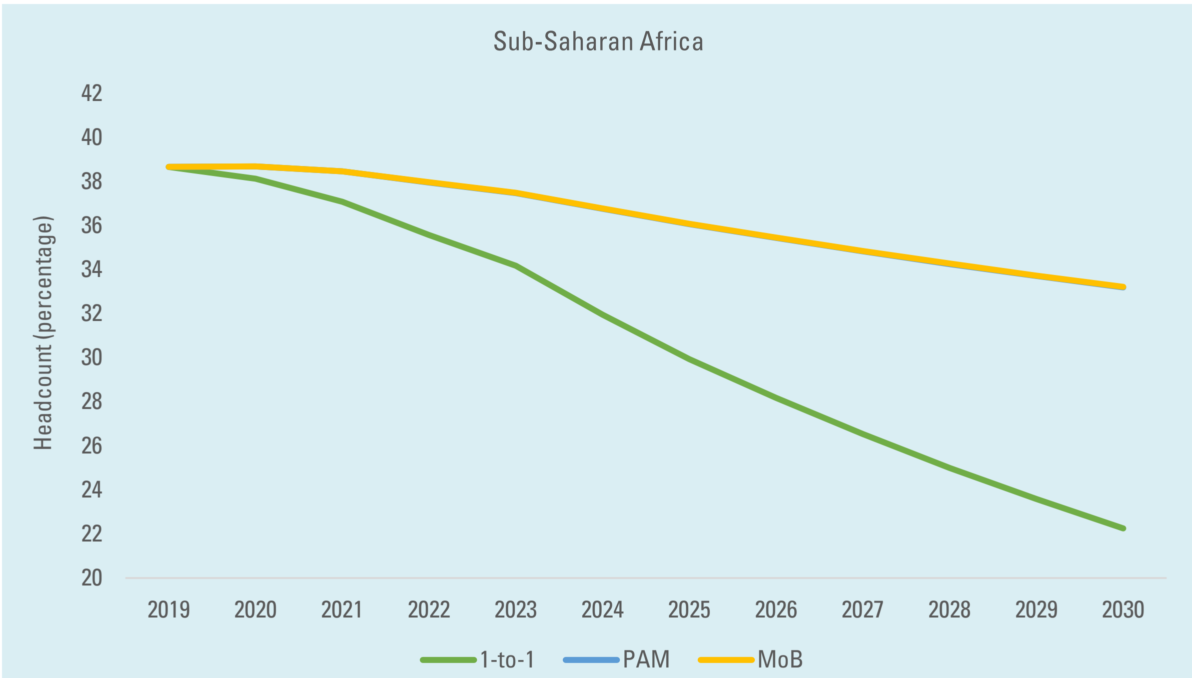
In normal cases, when PCE growth was positive, the passthrough ratio dampened and lowered the growth effect on poverty reduction. When the PCE growth was negative, such as in the year 2020, the attenuation effect of the passthrough ratio worked in the opposite direction. All regions – especially Latin America and the Caribbean that recorded a remarkable drop in PCE – witnessed significant hikes in poverty headcounts in 2020 under the full passthrough scenario. For the year 2021 and onwards, the PCE growth was projected to bounce back to above zero worldwide, leading to a reduction in the projected poverty headcounts under all different scenarios. Most critically, the alternative passthrough models had a large impact on the projected poverty rates at the global and regional levels, particularly when the effect of growth became compounded across longer time spans.

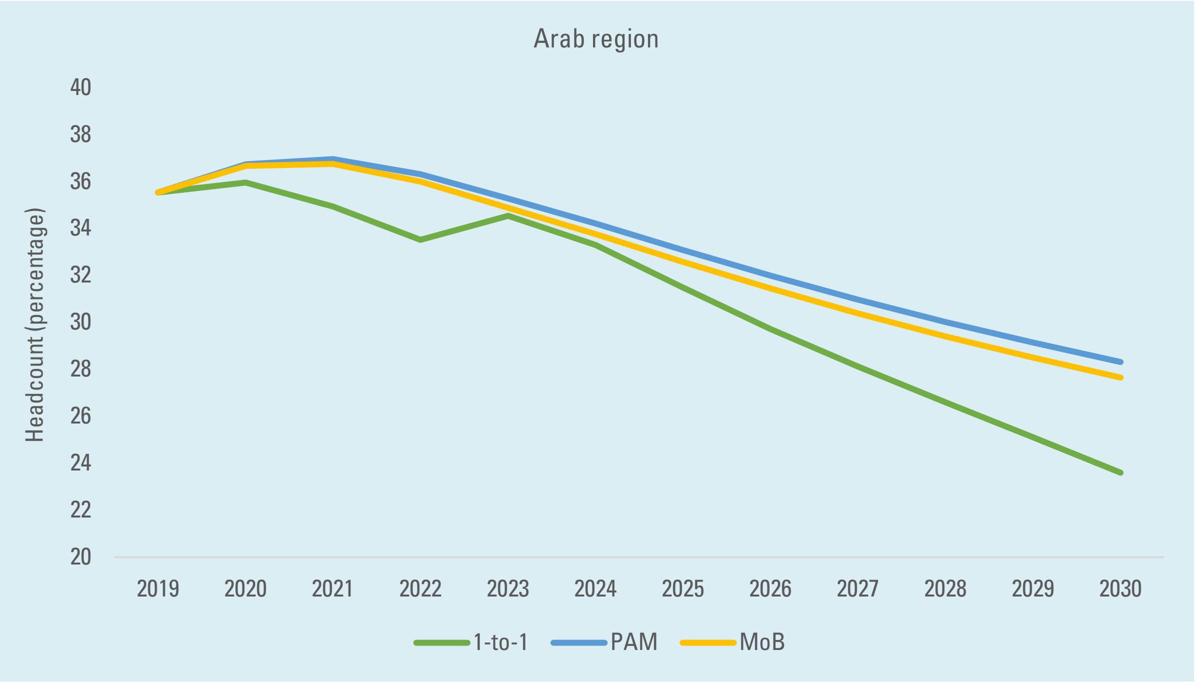
Figure 5. Poverty headcount ratios, per region and globally (2019-2030), as measured by national poverty lines

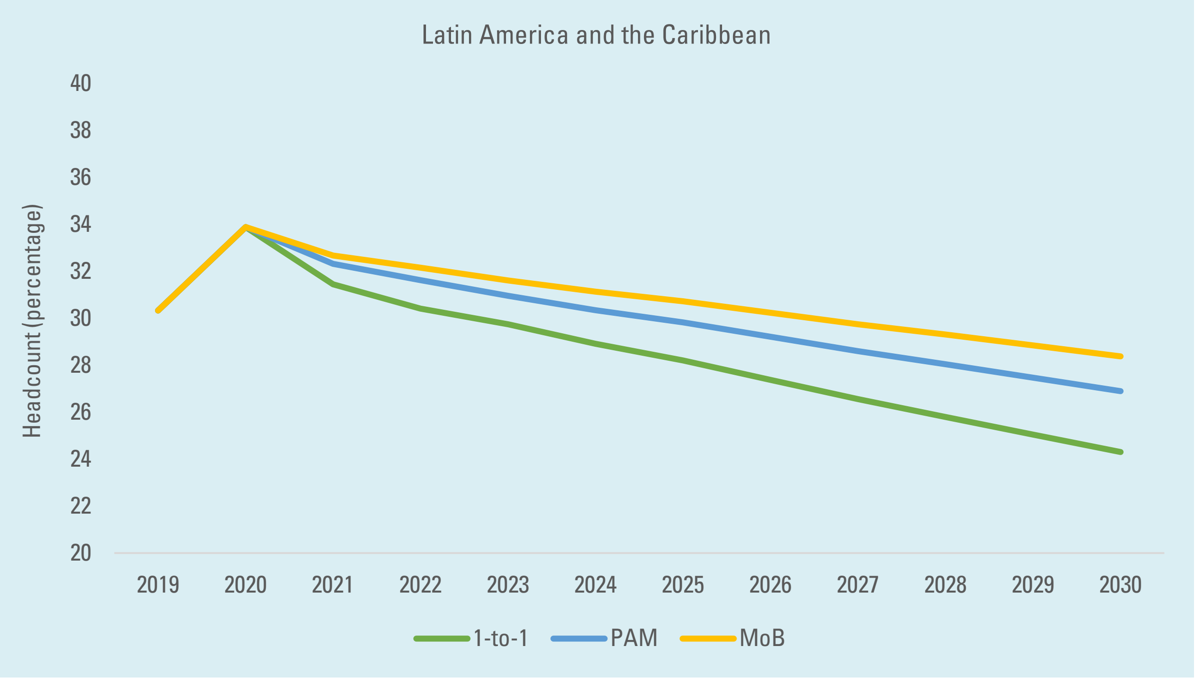


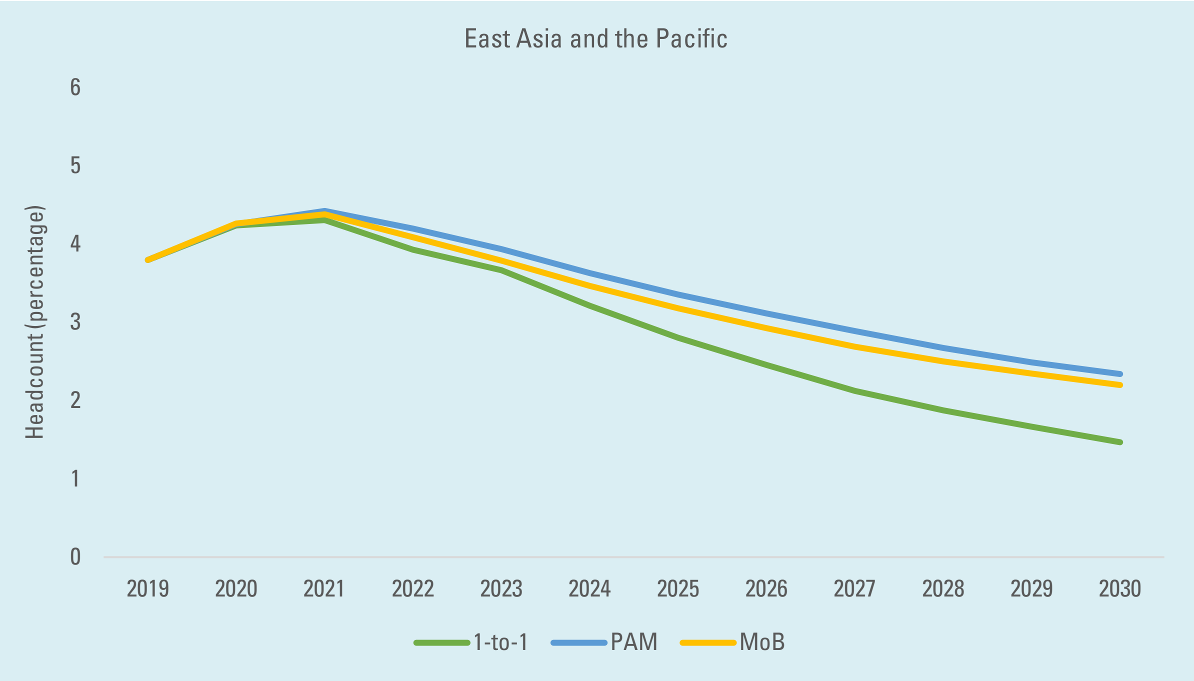


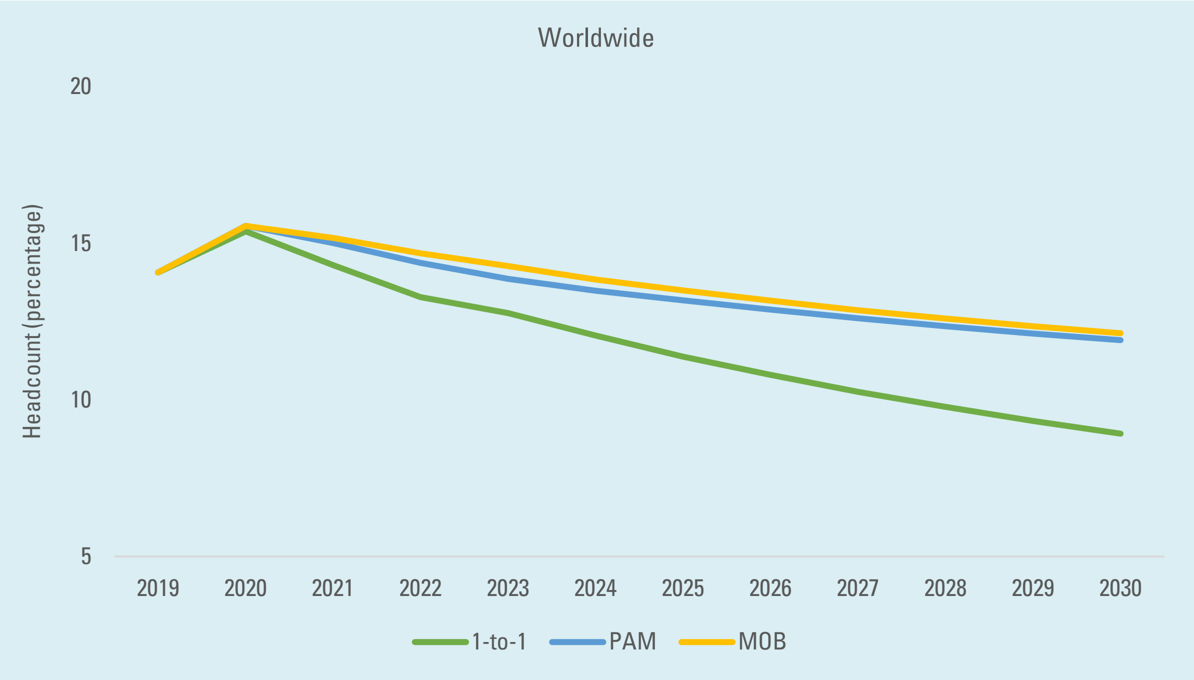

North America
14
13
12
11
10
9
8
7
Headcount (percentage)
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
1-to-1
PAM
MoB


Sub-Saharan Africa
42
40
38
36
34
32
30
28
26
24
22
20
Headcount (percentage)
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
1-to-1
PAM
MoB


Arab region
Headcount (percentage)
40
38
36
34
32
30
28
26
24
22
20
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
1-to-1
PAM
MoB

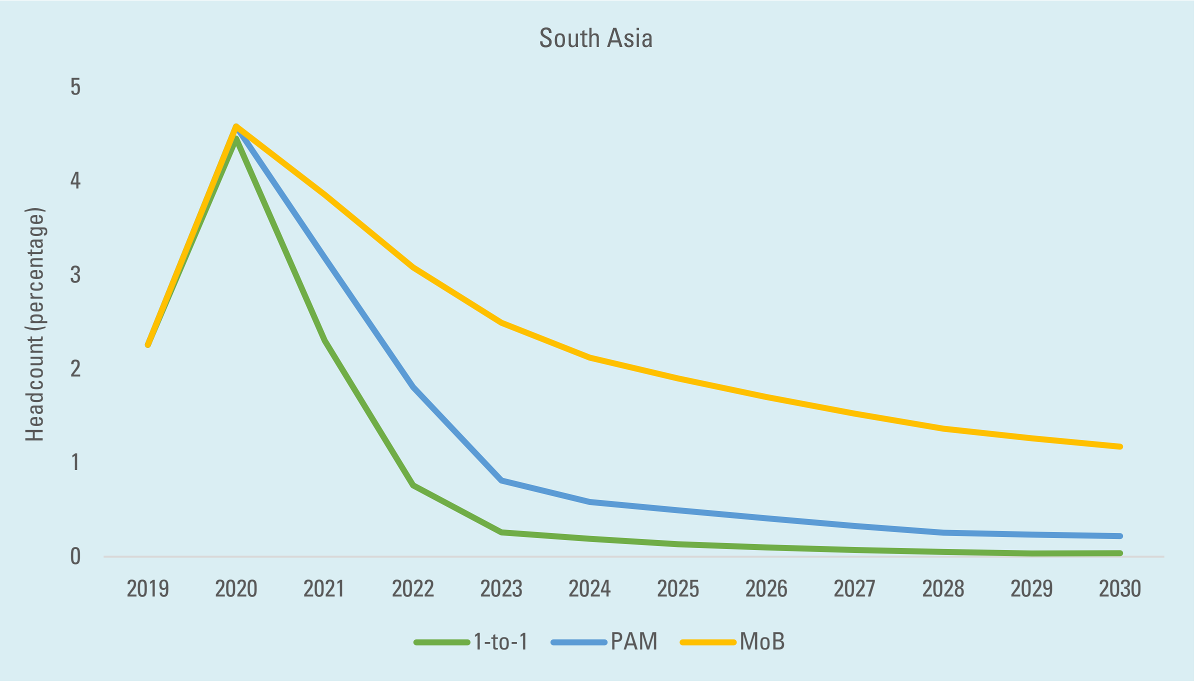

Latin America and the Caribbean
Headcount (percentage)
40
38
36
34
32
30
28
26
24
22
20
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
1-to-1
PAM
MoB

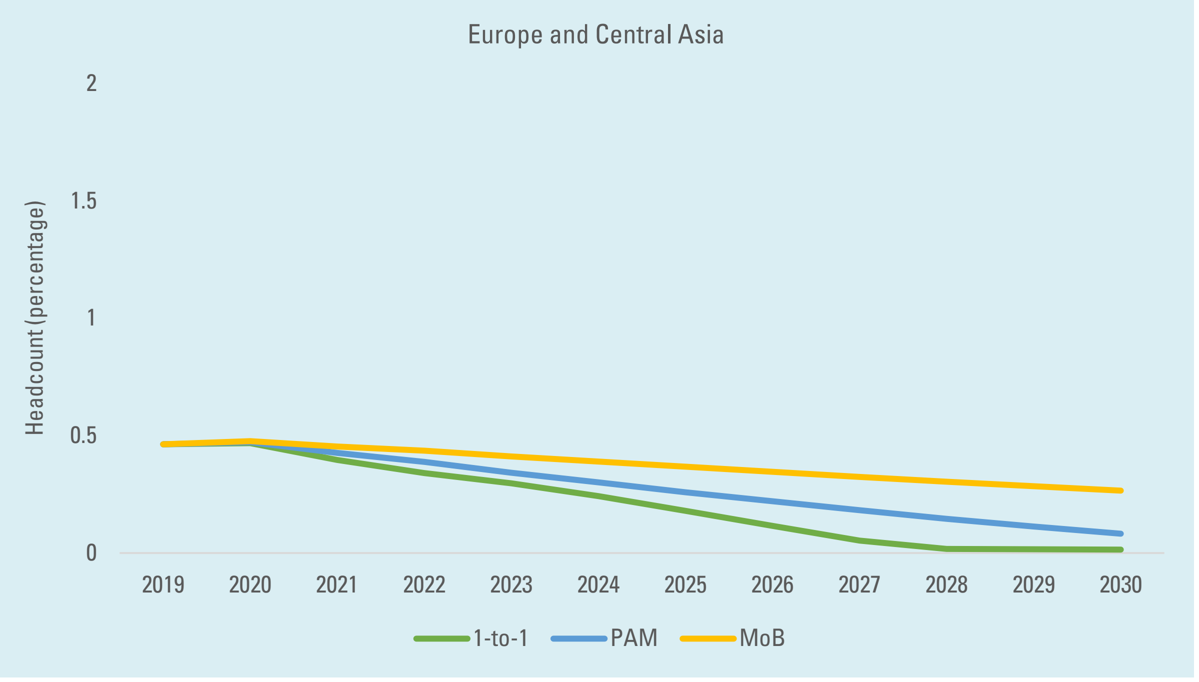


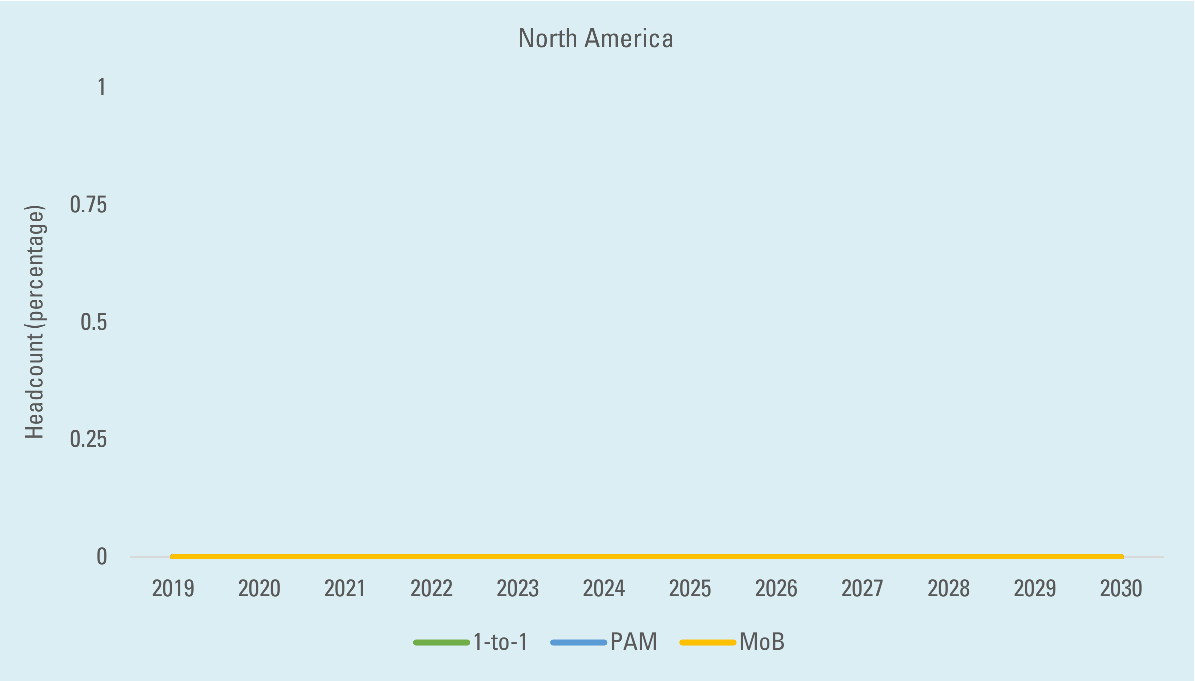


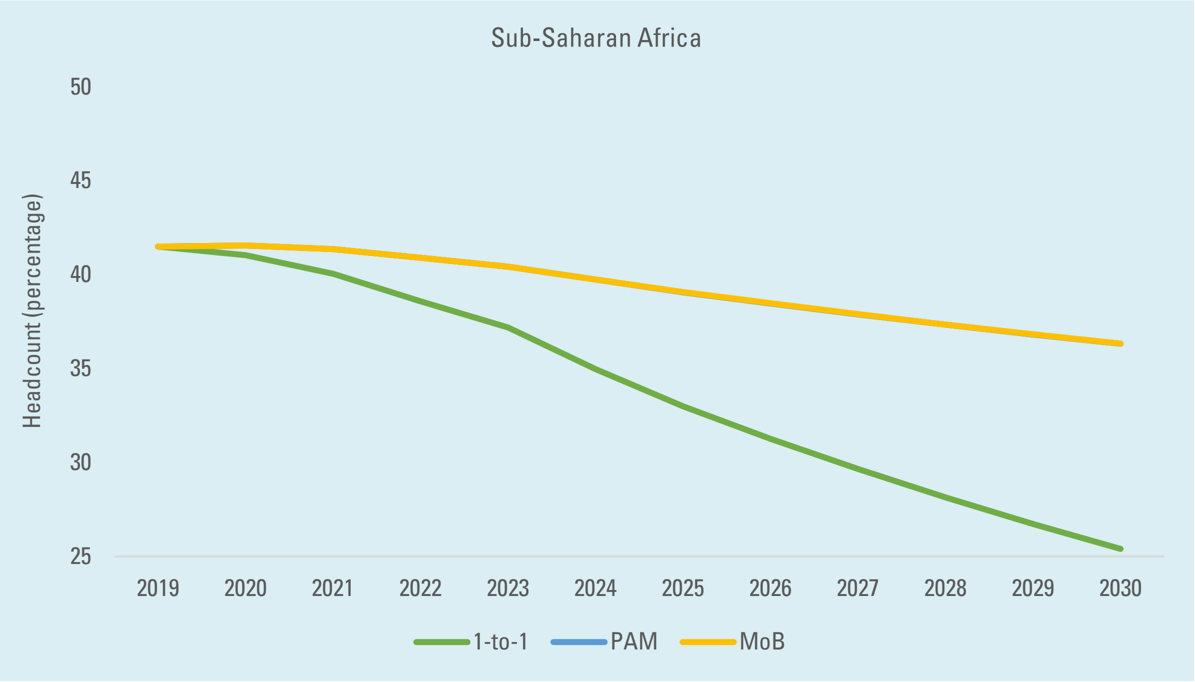
Source: Authors' calculations.

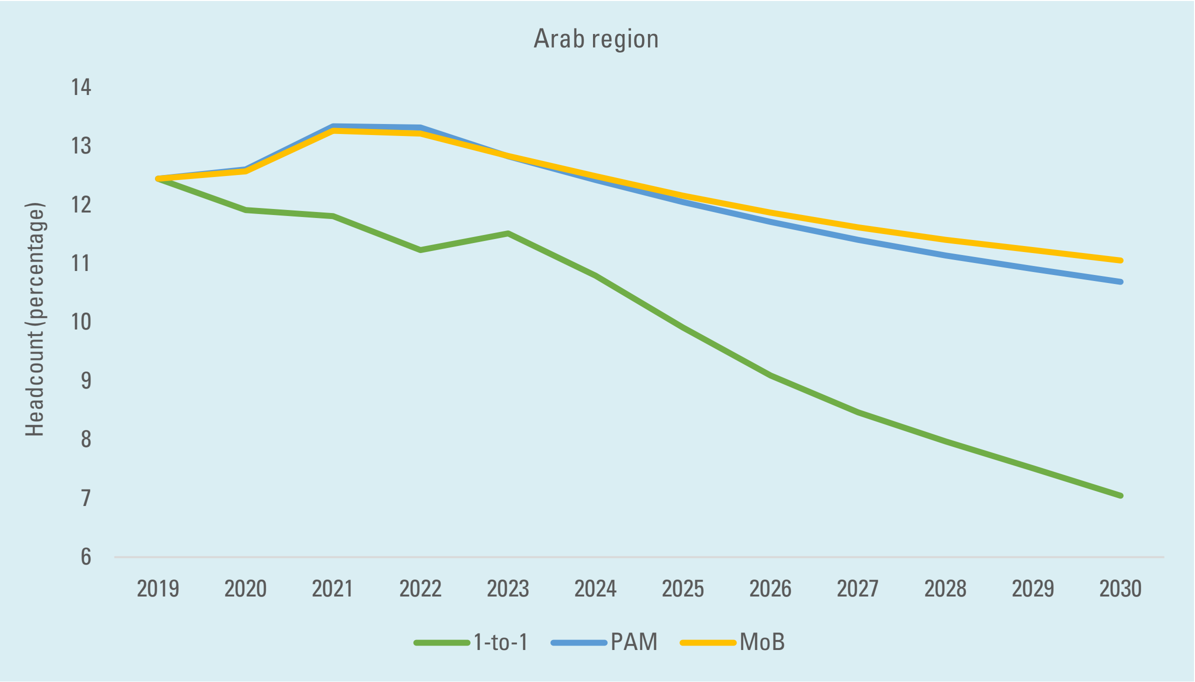
Figure 6. Extreme poverty headcount ratios, per region and globally (2019-2030), as measured by $1.9 (2011 PPP)

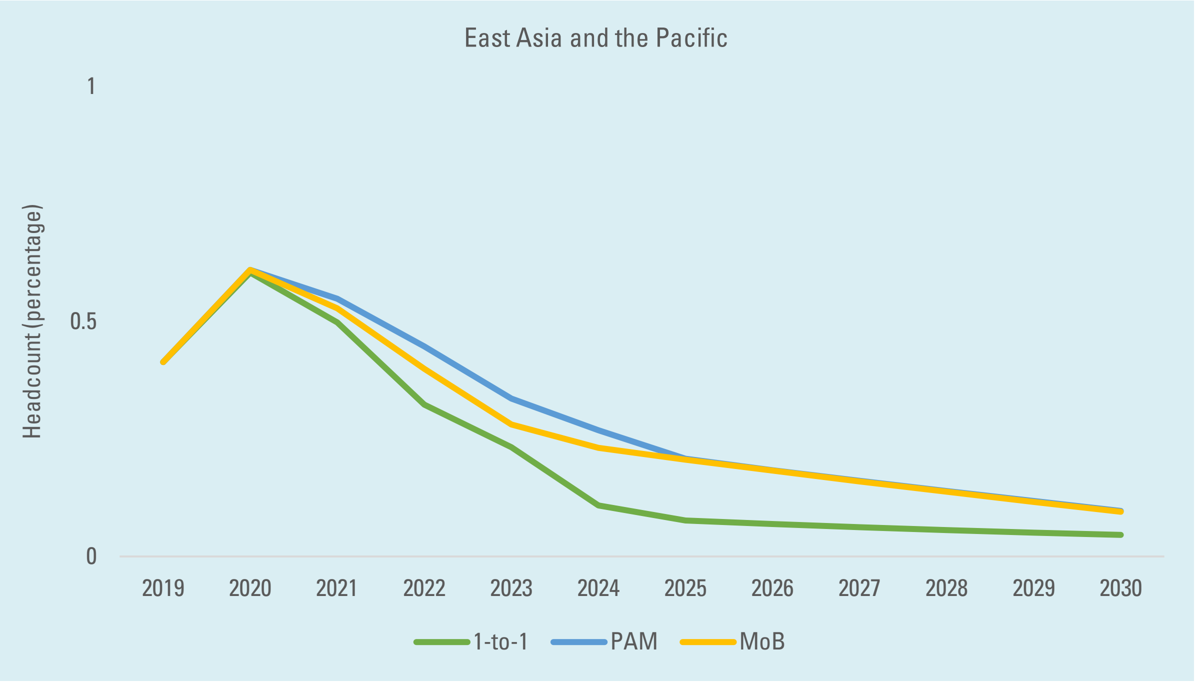


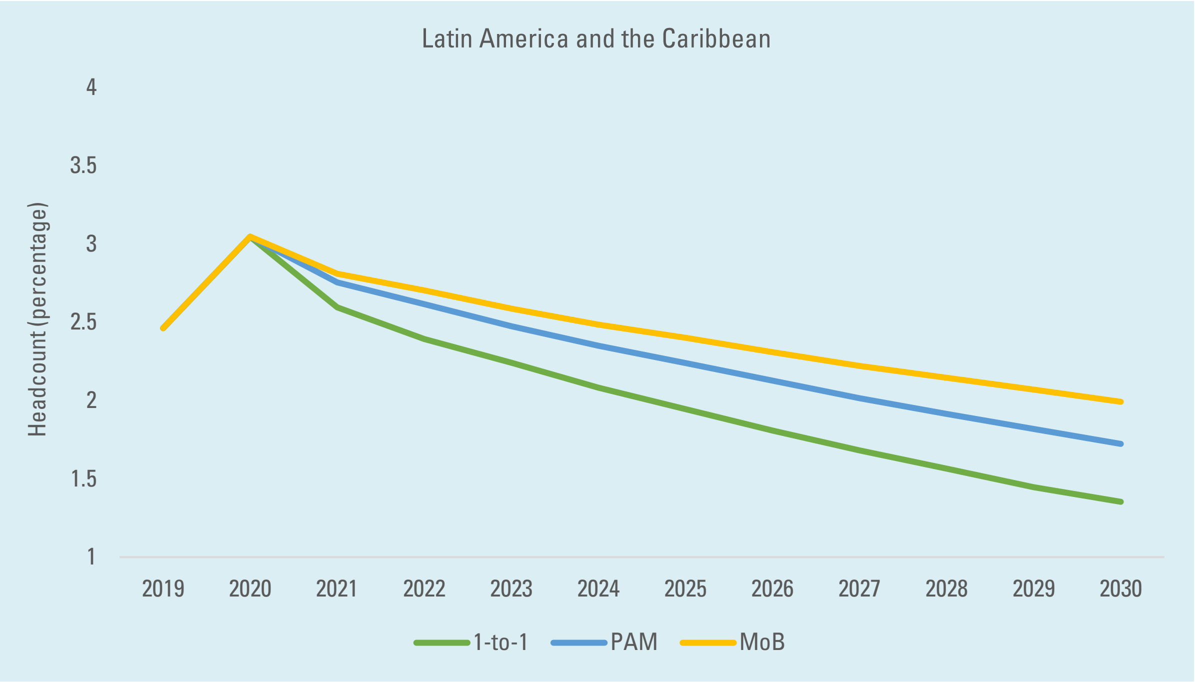


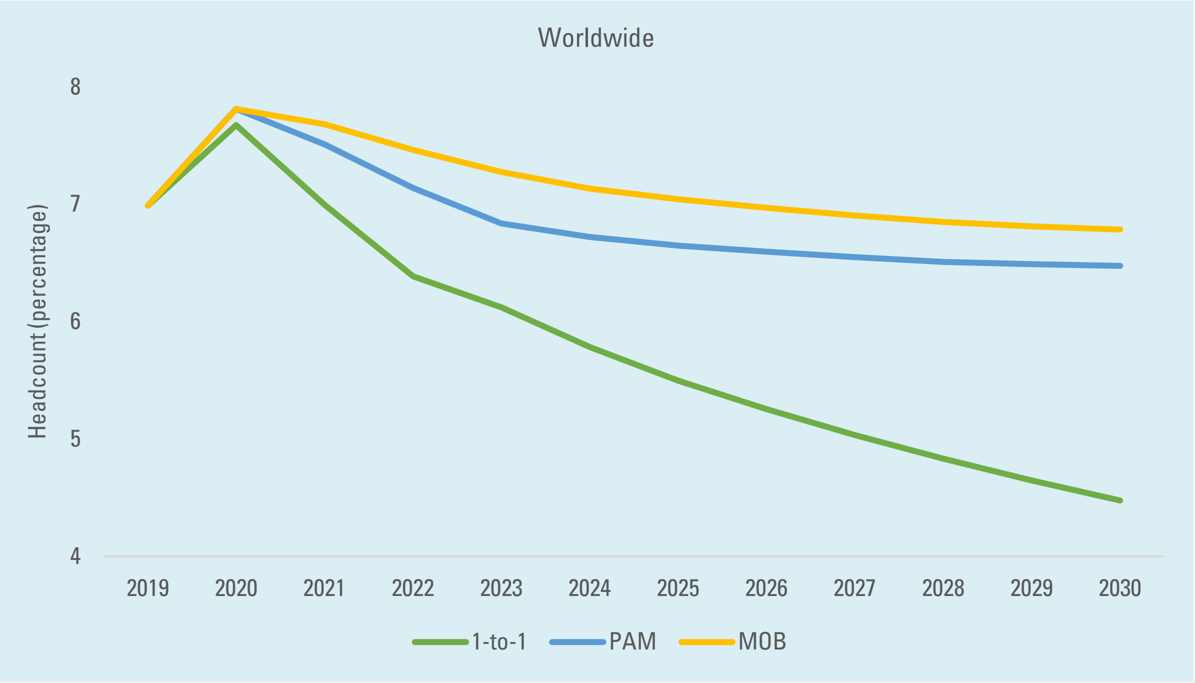

North America
Headcount (percentage)
1
0.75
0.5
0.25
0
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
1-to-1
PAM
MoB


Sub-Saharan Africa
Headcount (percentage)
50
45
40
35
30
25
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
1-to-1
PAM
MoB


Arab region
Headcount (percentage)
14
13
12
11
10
9
8
7
6
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
1-to-1
PAM
MoB

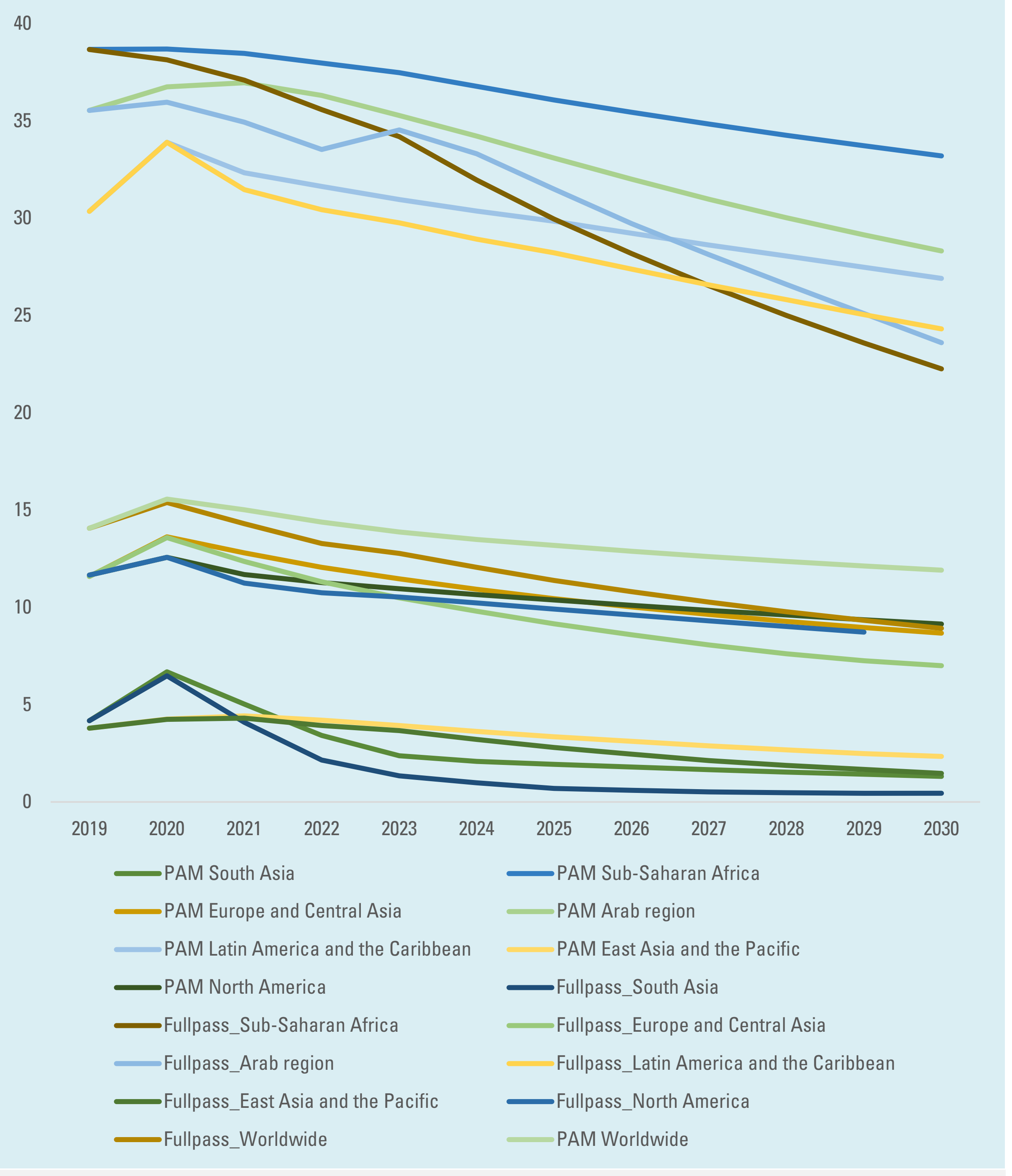

East Asia and the Pacific
Headcount (percentage)
1
0.5
0
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
1-to-1
PAM
MoB





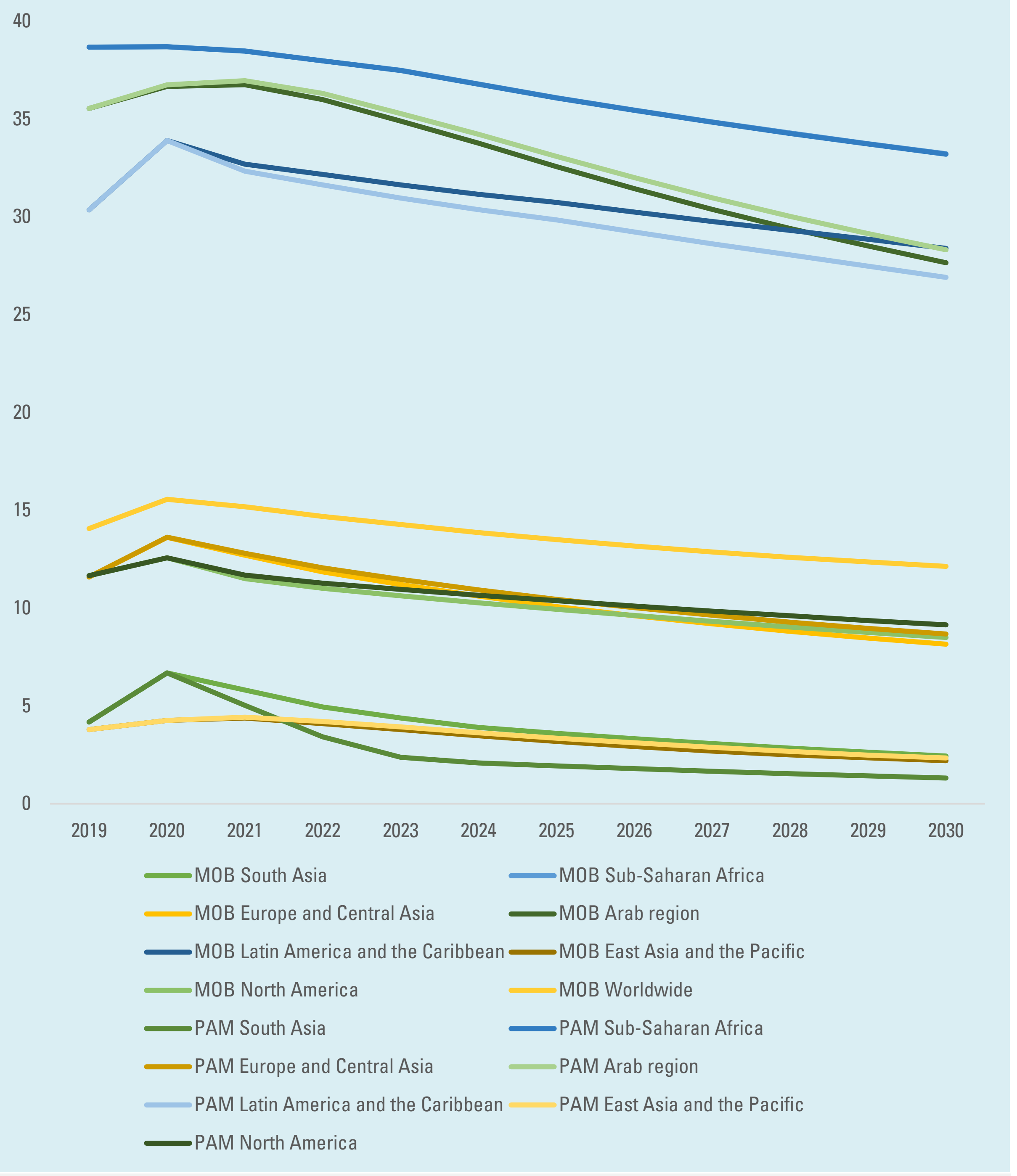
Source: Authors' calculations.

Figure 7. National poverty rates in all regions – full passthrough vs. PAM clustering



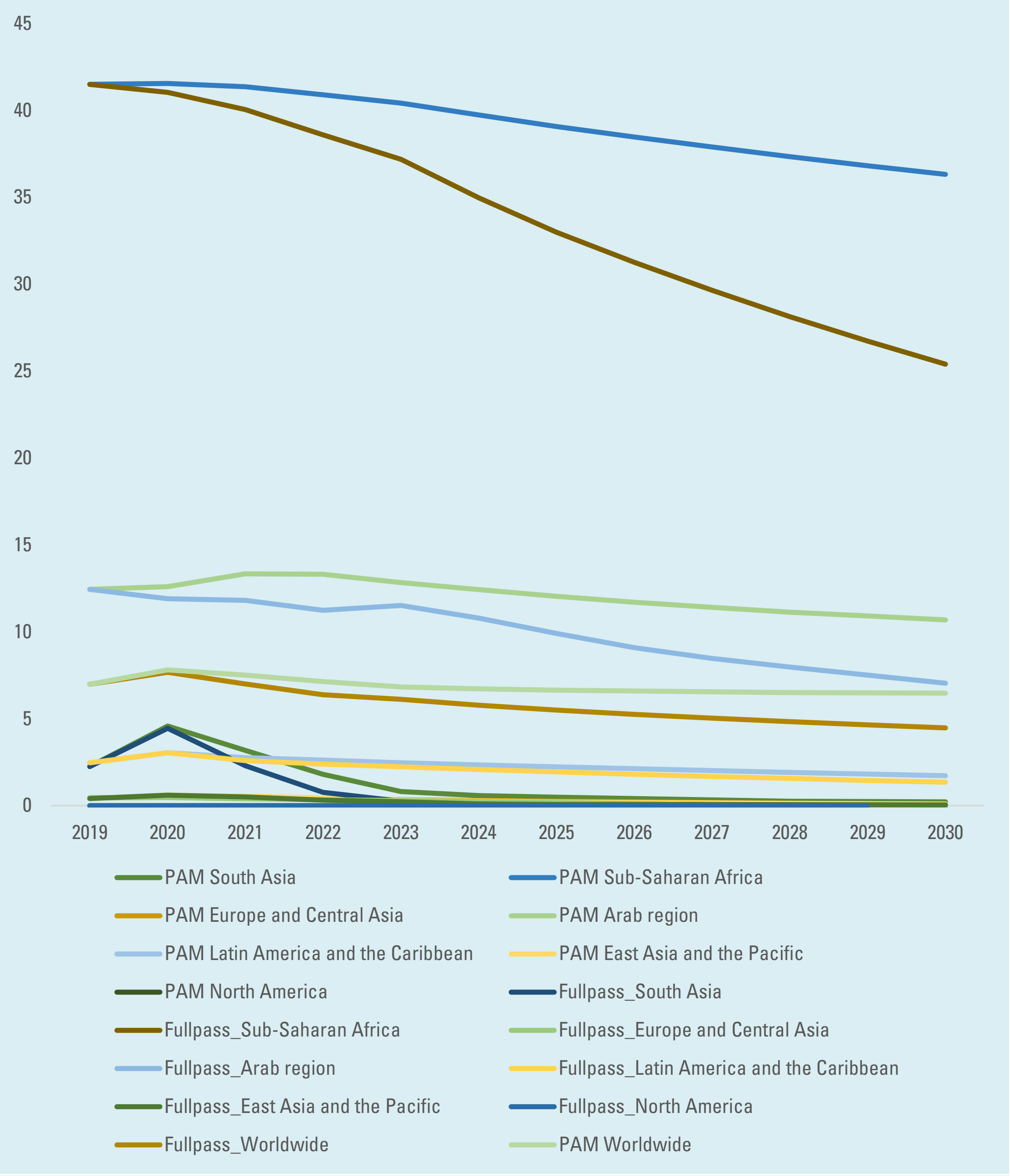
Source: Authors' calculations.

Figure 8. National poverty rates in all regions – MOB clustering vs. PAM clustering



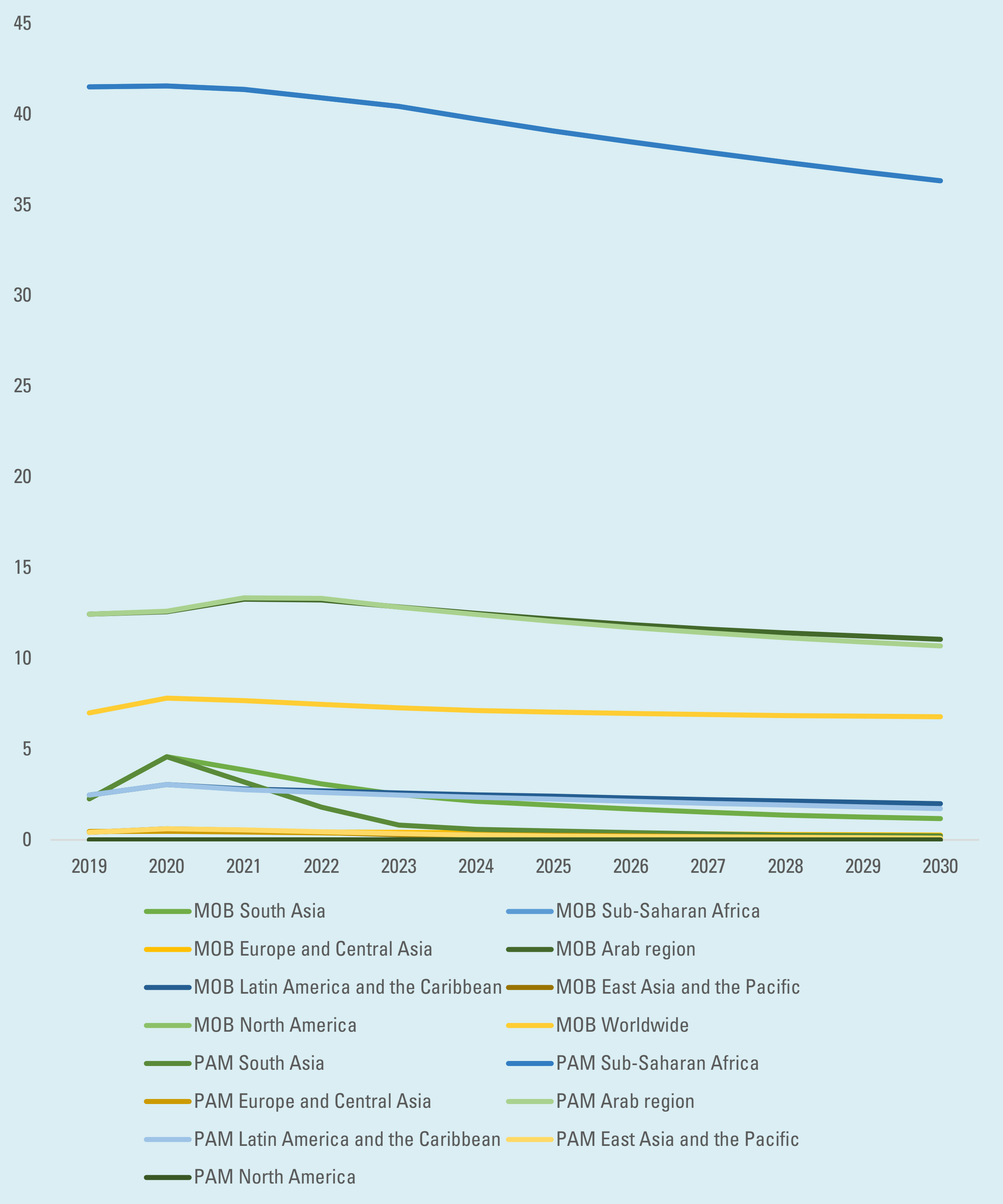
Source: Authors' calculations.

Figure 9. Extreme poverty rates in all regions – full passthrough vs. PAM clustering



Source: Authors' calculations.

Figure 10. Extreme poverty rates in all regions – MOB clustering vs. PAM clustering



Source: Authors' calculations.

B. Policy implications

These results contribute to our understanding of growth-inequality-poverty debates. Poverty iso-plots highlight the results visually, as they show the combination of inequality changes and growth changes resulting in the same level of poverty headcounts. The flatness of the curves (figure A1.5) implies the relative importance of growth in affecting poverty. The steeper areas (figure A1.6), on the other hand, show the opposite situation. For these countries, policymakers are advised to focus on greater inclusion, lower inequality and concentration of income as the primary tools for poverty reduction.

Of all countries that had the lowest passthrough ratios (0.304) using the MOB subgroup clustering method, the majority scored higher on GEP compared to the inequality elasticity of poverty reduction. In fact, results indicated that 56 per cent of countries belonging to this cluster had higher GEP (table A1.4). From a policy standpoint, in order to reduce poverty more effectively in these countries, policymakers should focus on growth-enhancing reforms. This is not the case for other subgroups, where the focus should rather be on income redistribution and inclusivity. Our passthrough results distort these policy recommendations to some extent. Unsurprisingly, applying the passthrough reduces the effect of growth on poverty reduction. However, the important conclusion is at the policy level. To elaborate more, the following example provide an illustration: Sudan (Cluster I) had the GEP reduction of 1.89 in absolute value. As a result, an increase in mean consumption expenditure of 1 per cent was expected to decrease headcount ratio by 1.89 per cent. However, having a passthrough ratio of 0.304 changed the effective GEP to 0.57 per cent, significantly lower than the effect induced by a 1 per cent change in inequality.

We evaluated the relative effects of growth and inequality-targeting policies for the year 2020. In countries where the inequality elasticity of poverty reduction exceeded the GEP in absolute value, this relationship was overturned in 63 per cent of countries once the passthrough factors were taken into account. Having a low passthrough factor can impact a country’s prescribed pathway toward inequality-centred poverty reduction policies.

5. Conclusion

This study has highlighted the fact that growth in national accounts does not translate one-to-one to growth in household consumption expenditures. and the implications this has for poverty projections and the role of growth and distribution policies. The study has evaluated several approaches to effectively measuring the relationship between growth trends in surveys and in national accounts, using alternative estimation specifications and definitions of variables and data. The relative accuracy and robustness of these methods was assessed, and two unsupervised clustering methods were selected so as to provide plausible, robust and efficient results. The two sets of results were similar. Analysis at the level of world regions clearly outperformed country-level estimations. Applying the methods to a large macroeconomic dataset, the study derived passthrough ratios for various geographic units: regional levels of various degrees of aggregation or economic country-groupings. While the analysis started from a stylized fact that passthrough ratios differ markedly across world regions, as additional country attributes were introduced – including poverty headcount ratio, mean/median income/consumption expenditure and inequality – the role of regional differences declined, and the other variables became more influential in determining the passthrough rates.

Regardless of the estimation method used, for developing and low-income regions, especially the Arab region and Sub-Saharan Africa, the passthrough ratios of aggregate growth to household incomes/consumption expenditures were found to be very low. Industrialized countries in Europe, Central Asia, East Asia and the Pacific had higher passthrough rates. Digging deeper, the study concluded that it was the combination of low median incomes, high inequality and high poverty headcount ratios that was associated with low passthrough rates.

Such insights are crucial for understanding the patterns of trickle through from aggregate economy-wide to household outcomes, and for inferring systematic, systemic leakages in countries with different characteristics. These insights can be applied to other problems, such as forecasting or simulating the distributions of other economic outcomes from surveys – such as wealth or non-monetary standards of living – based on national accounts projections.

The study concluded that under the alternative estimation methods, most world regions witnessed a high jump in poverty headcounts in 2020. For the years 2021-2030, the poverty headcounts are projected to decline everywhere, but the rate of decline is expected to be impacted significantly by the limited passthrough from aggregate growth to household livelihoods in poorer regions.

The policy implications of this study are that a faster recovery from the ongoing COVID-19 crisis and robust poverty reduction on the path to meeting the SDGs may require going beyond business-as-usual growth-centred policies: States must tackle factors that limit the trickle through. The findings in this study thus lend further strength to the efficacy of pro-growth policies as the main vehicle for poverty reduction, especially in poor high-inequality countries with low passthrough rates.

Finally, several follow-up research activities can be envisaged which build on the methodology and utilize these findings. For example, the passthrough forecasting methodology can be refined further by improving the model specification and particularly by examining the link between the size of the passthrough and under-reporting of top incomes. Also, the poverty story would not be complete without an equivalent analysis of inequality projections, which is inherently more complex. The forecasting methodology in this paper will provide the logical basis for ESCWA's forthcoming money metric poverty projection tool, a web-based system with a user-friendly interface where users can simulate the impact of various growth and inequality scenarios on money metric poverty at national, regional and global levels.

Annex 1. Supplementary descriptive statistics

Country surveys used in the study (Pooled data)

Algeria (1988, 1995, 2011); Angola (2009, 2018, 2016); Argentina (2016, 2019); Armenia (2004, 2007, 2010, 2016, 2019); Azerbaijan (2001, 2005); Bangladesh (2000, 2005, 2010, 2016); Belarus (2000, 2005, 2010, 2015, 2019); Belize (1993, 1996, 1999); Benin (2003, 2011, 2015); Bhutan (2003, 2012, 2017); Bolivia (2005, 2011, 2015, 2019); Bosnia and Herzegovina (2001, 2007, 2011); Botswana (1986, 1993, 2009, 2016); Brazil (2012, 2015, 2019); Burkina Faso (1994, 2009, 2014); Burundi (1999, 2006, 2014); Carbo Verde (2002, 2007, 2015); Cameroon (1996, 2007, 2014); Canada (2004, 2010, 2017); Central Africa Republic (2008); Chad (2003, 2011); Chile (2000, 2011, 2017); China (1996, 2005, 2010, 2012, 2014, 2016); Colombia (2002, 2010, 2014, 2019); Comoros (2014); Democratic Republic of Congo (2005, 2011, 2012); Costa Rica (2011, 2014, 2017, 2019); Cote d'Ivoire (1985, 1995, 2008, 2015); Djibouti (2002, 2013, 2017); Dominican Republic (2000, 2004, 2010, 2019); Ecuador (2007, 2010, 2014, 2019); Egypt (1991, 2000, 2010, 2018); El Salvador (2000, 2010, 2019); Estonia (2014, 2018); Eswatini (2001, 2009, 2016); Ethiopia (1995, 2005, 2011, 2016); Fiji (2003, 2009, 2013); Gabon (2005, 2017); Gambia (1998, 2010, 2015); Georgia (2005, 2010, 2015, 2019); Ghana (1992, 2006, 2013, 2017); Guatemala (2000, 2006, 2014); Guinea (1994, 2002, 2012); Guyana (1993, 1998); Guinea-Bissau (2002, 2010); Haiti (2012); Honduras (2001, 2006, 2010, 2018); India (1994, 2005, 2010, 2012); Indonesia (1998, 2002, 2006, 2010, 2014, 2019); Iran (1986, 1998, 2016, 2017); Iraq (2007, 2012); Italy (2005, 2010, 2015, 2017); Jamaica (1993, 1999, 2004); Japan (2008, 2013); Jordan (1987, 1997, 2006, 2010); Kazakhstan (2001, 2005, 2010, 2018); Kenya (1992, 1997, 2005, 2016); Kiribati (2006); Kosovo (2012, 2014, 2018, 2013); Kuwait (2013); Kyrgyz Republic (2006, 2010, 2015, 2019); Lao People's Democratic Republic (1992, 2002, 2012, 2018); Lebanon (2012); Lesotho (2003, 2017); Liberia (2007, 2016); Lithuania (2016, 2018); Madagascar (1993, 2010, 2012); Malawi (1998, 2010, 2016); Malaysia (2016), Maldives (2003, 2010); Mali (2001, 2010); Mauritania (1996, 2008, 2014); Mexico (2006, 2010, 2014, 2018); Federation States of Micronesia (2005, 2013); Moldova (2005, 2010, 2015, 2018); Mongolia (1995, 2010, 2014, 2018); Morocco (1995, 2010, 2014, 2018); Morocco (1985, 1991, 2001, 2014); Mozambique (1996, 2009, 2014); Myanmar (2015, 2017); Namibia (1994, 2010, 2010, 2015); Nauru (2013); Nepal (1996, 2003, 2010); Nicaragua (2001, 2009, 2014); Niger (1993, 2005, 2011, 2014); Nigeria (2004, 2010, 2019); Pakistan (2002, 2008, 2011, 2016); Panama (2000, 2010, 2015, 2019); Papua New Guinea (1996, 2010); Paraguay (1997, 2003, 2010, 2015, 2019); Peru (2004, 2010, 2016, 2019); Philippines (1985, 1994, 2009, 2018); Russian Federation (2000, 2005, 2010, 2015, 2018); Rwanda (2000, 2011, 2017); Samoa (2002, 2008, 2013); Sao Tome and Principe (2010, 2017); Saudi Arabia (2018); Senegal (20001, 2011); Sierra Leone (2003, 2011, 2018); Solomon Islands (2005, 2013); Somalia (2017); South Africa (2005, 2010, 2015); South Sudan (2009, 2017); Sri Lanka (1991, 1996, 2010, 2016); St. Lucia (1995, 2016); Sudan (2009, 2014); Suriname (1999); Switzerland (2007, 2010, 2013, 2018); Seychelles (2013, 2018)Syrian Arab Republic (2004); Tajikistan (2003, 2009, 2015); Tanzania (1992, 2000, 2012, 2018); Thailand (2000, 2006, 2010, 2018); Timor-Leste (2001, 2007, 2014); Togo (2006, 2011, 2015); Tonga (2001, 2009, 2015); Trinidad and Tobago (1988, 1992); Tunisia (1985, 1995, 2010, 2015); Turkmenistan (1998); Tuvalu (2010); Uganda (1992, 2009, 2012, 2017); Ukraine (2002, 2006, 2010, 2015, 2019); United Arab Emirates (2018); United States (1986, 1997, 2007, 2010, 2015, 2018); Vanuatu (2010); Venezuela (1998, 2001, 2003, 2006); Vietnam (1993, 2002, 2010, 2018), West Bank (2010, 2017); Republic of Yemen (2005, 2014); Zambia (1996, 2007, 2010, 2015); Zimbabwe (2011, 2019).

Table A1.1 Descriptive statistics of the growth spells

	T_{oldest}	T_{latest}
Minimum spell length, years [country(ies) to which the minimum spell-length belongs]	1 Uzbekistan [2002-2003]	1 Honduras [2018-2019] Thailand [2018-2019] Türkiye [2018-2019] Etc.
Maximum spell length, years	18 Islamic Republic of Iran [1998-2016]	16 Algeria [1995-2011] Central African Republic [1992-2008]
Range	[1990,2018]	[1992,2019]
Arithmetic average, years	3.8	6.04

Source: Authors' calculations.

Table A1.2 Categorical variables descriptive statistics

Region	Number of countries	Welfare measurement		Poverty lines		Income group classification			
		Consumption expenditure	Income	Absolute	Relative	High	Upper middle	Lower middle	Low
Arab region	21	17	4	13	-	6	3	8	4
East Asia and the Pacific	30	22	8	24	3	8	10	12	-
Europe and Central Asia	51	17	34	23	28	31	15	4	1
Latin America and the Caribbean	27	4	23	27	-	6	16	4	1
North America	2	-	2	2	-	2	-	-	-
South Asia	10	10	-	9	1	-	2	7	1
Sub-Saharan Africa	42	41	1	41	-	2	4	16	20
Total	183	111	72	137	34	55	50	51	27

Source: Compiled by the authors.

Table A1.3 Numerical variables descriptive statistics

Variable	Min.	Q1	Median	Mean	Q3	Max.	NAs	Standard deviation
Headcount (*percentage*)	0.7783	15	25.3	29.77	41.85	83.3	26	17.89
Poverty line (PPP$/day)	0.7297	2.23	4.06	6.71	7.27	36.38	26	6.99
Mean income (PPP$/month)	22.6	124.5	259.2	478.4	564.2	3294.3	1	545.65
Median income (PPP$/month)	16.07	90.05	181.97	367.64	398.87	3106.87	6	450.38
Gini index (*percentage*)	24.63	32.86	37.66	39.13	44.14	65.76	3	8.37
Population (millions)	10,279	3,400,434	10,474,410	52,951,301	38,041,757	859,247,883	-	129,109,433
Population density (*percentage*)	1.48	30.244	73.425	160.375	144.14	6987.238	-	462.91
Urban population (*percentage*)	7.83	36.65	54.54	54.31	73.67	100	-	22.76
Age dependency ratio (*percentage*)	16.31	48.56	57.03	63.38	78.66	112.51	-	19.18

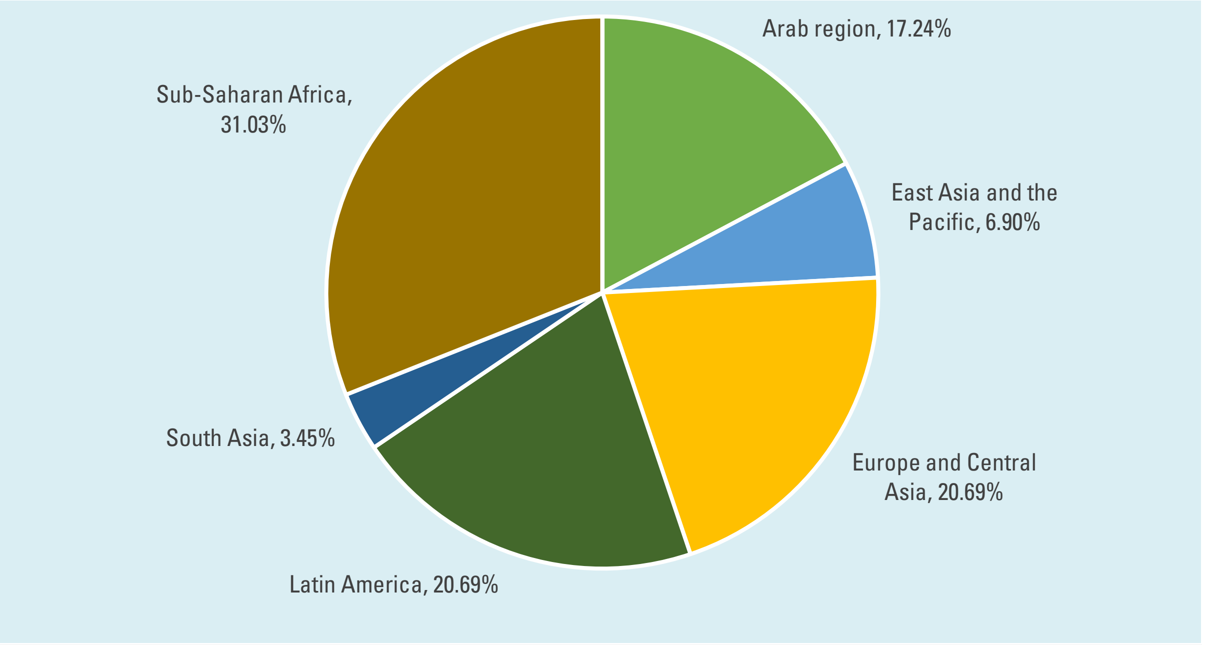
Source: Authors' calculations.

Table A1.4 Pre and post passthrough adjustment elasticity results at the subgroup clusters level – year 2020

Subgroup level clusters	Passthrough rate	Pre-adjustment, including the effect of passthrough – percentage of countries whose headcount is more elastic		Post adjustment – percentage of countries whose headcount is more elastic	
		To mean income (*percentage*)	To Gini index (*percentage*)	To mean income (*percentage*)	To Gini index (*percentage*)
I	0.304	56	44	23	77
II	0.629	33	67	21	79
III	0.651	35	65	0	100
IV	0.675	44	56	15	85
V	0.789	40	60	0	100

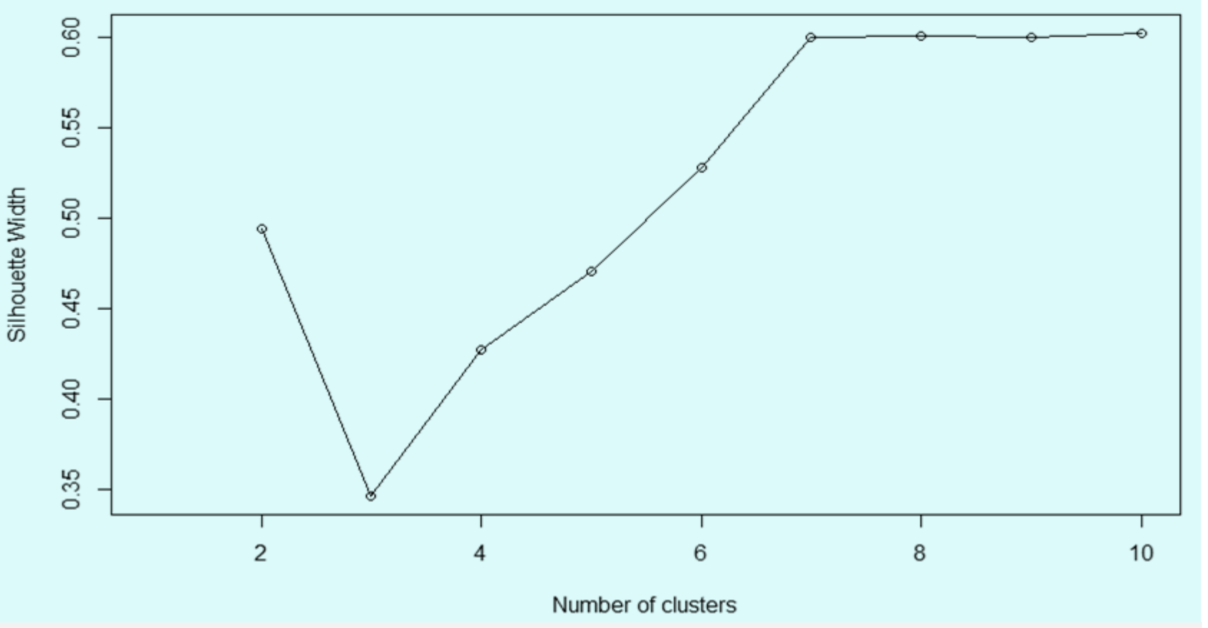
Source: Authors' calculations.

Figure A1.1 Passthrough outliers: distribution by world region



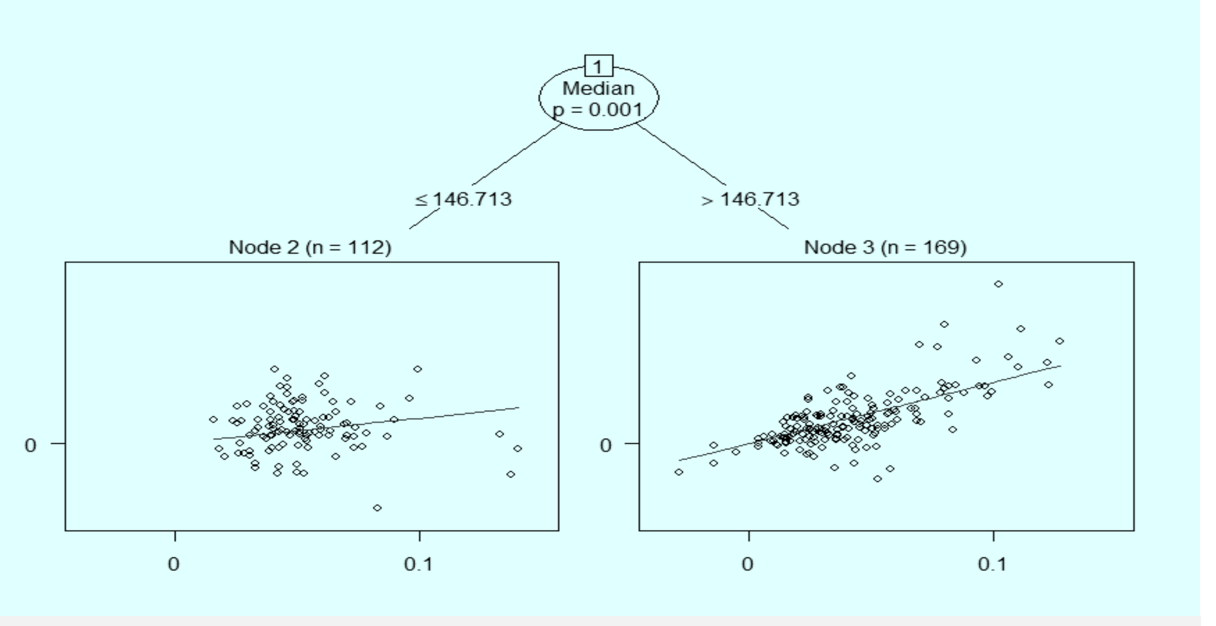
Source: Authors' calculations.

Figure A1.2 Silhouette analysis for choosing optimal number of clusters



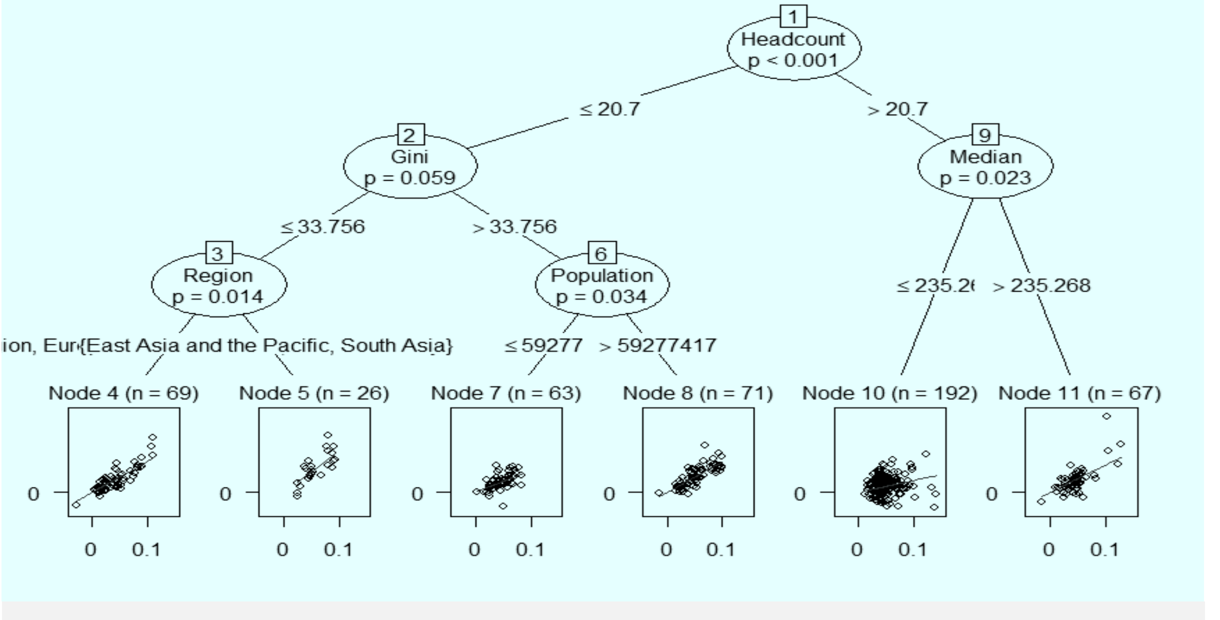
Source: Authors' calculations.

Figure A1.3 Dendrogram for MOB clustering with limited number of observations



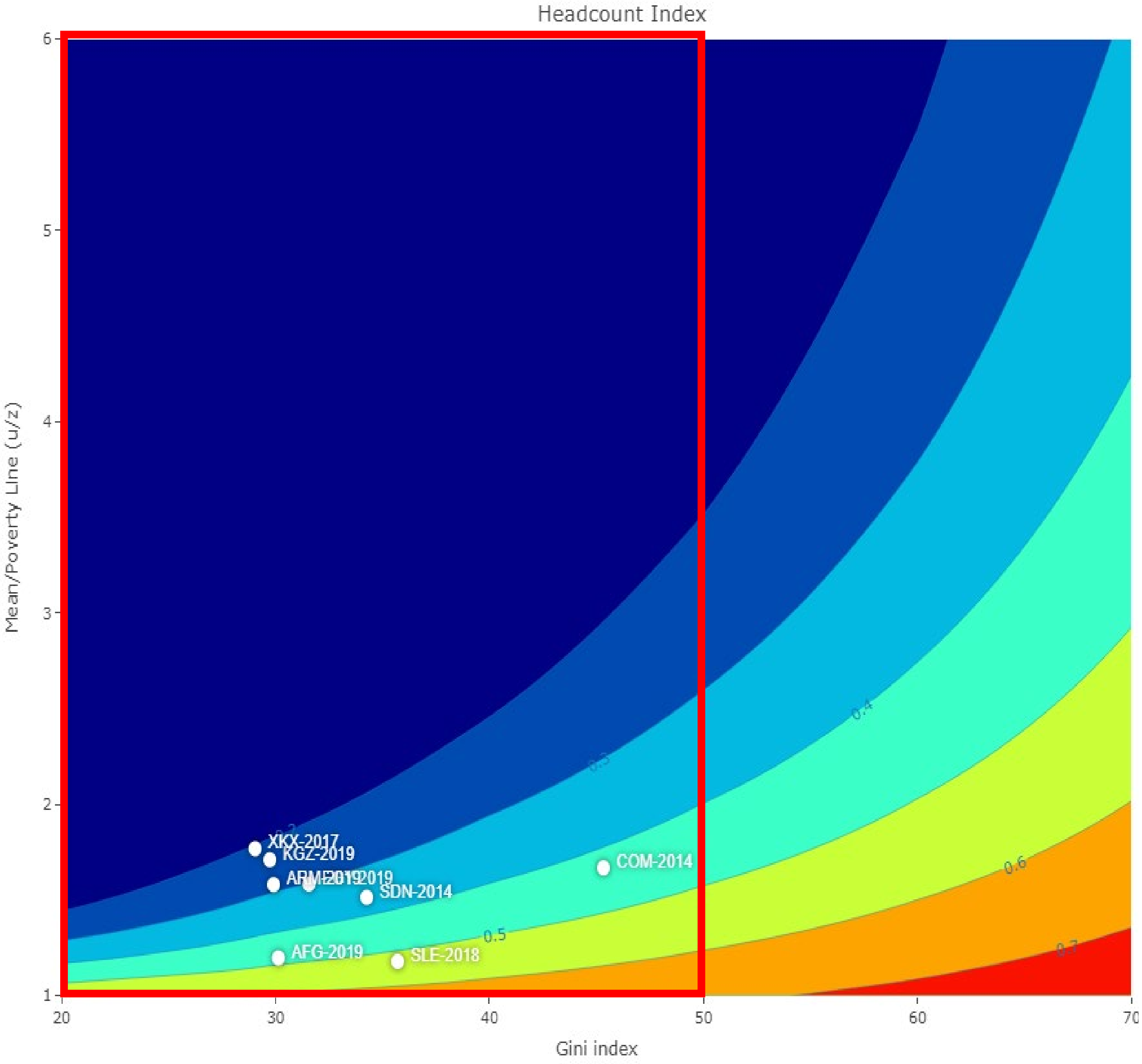
Source: Authors' calculations.

Figure A1.4 Dendrogram for clustering based on statistical testing for expanded dataset



Source: Authors' calculations.

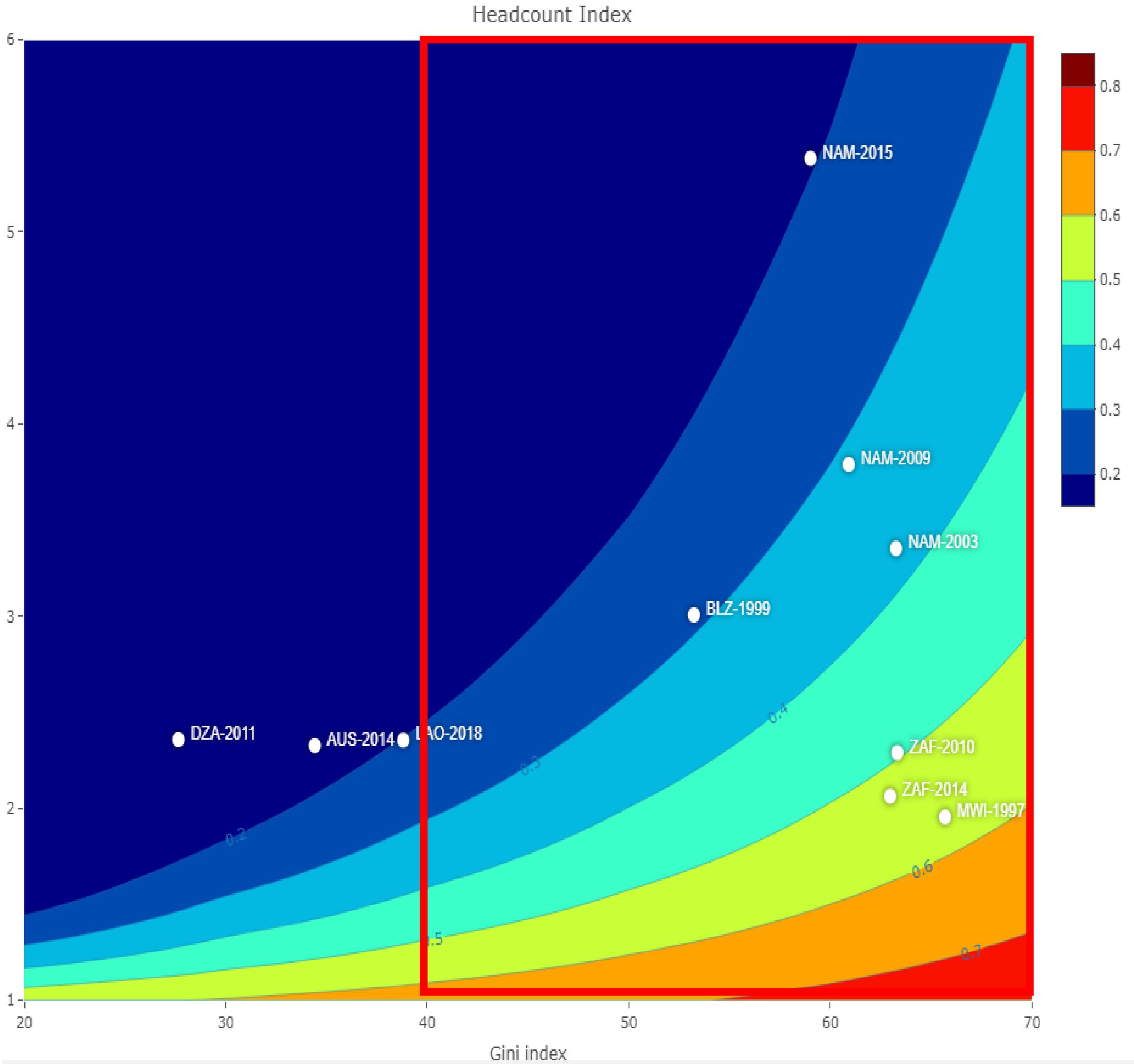
Figure A1.5 Poverty iso-plots – flat section in red frame



Source: Authors' calculations.

The flatness section of the curves illustrates the relative role of growth in shaping poverty rates. For illustrative reasons, some country results were added to the figure. For these countries, policymakers need to focus on economic reforms that favour growth in national accounts. Some of the countries are characterized by high headcount ratios or low mean income to poverty line ratios associated with low-to-medium inequality.

Figure A1.6 Poverty iso-plots – steep section in red frame



Source: Authors' calculations.

The steeper area shows the opposite. For these countries, policymakers should focus on addressing the issue of income inequality in order to reduce poverty more efficiently.

Annex 2. Cross-validation

The data was divided into training and testing sets (80 per cent and 20 per cent). The first subset was used for fitting the model and the other for testing. This was important for testing the model's performance.

To study the stability and robustness of the models at the regional level, a cross-validation technique was applied. The model was fitted multiple times (three iterations), and each time on a different randomly selected training set.

As we needed all regions to be represented by a reasonable number of observations, regional stratification was also applied. This was important, as the frequency of surveys chosen in our initial data set was unfortunately not homogenous across regions. As the training set was chosen at random, regions with less-frequent income surveys had a lower probability of being selected. Overall, the training subset of observations changed at each run and we needed to ensure that each region was still being represented when performing the cross validation.

For the PAM model, at the regional level analysis the passthrough results computed from the clusters that were formed with the training data were similar to the passthroughs computed from the observed data set for all runs (I, II and III, I being the analysis conducted in the document).

Aside from the regional-level comparison, the figure highlights the sensitivity of the MOB method to the randomness that prevailed from the cross validation (while also controlling for region stratification). However, the general conclusions were conserved, in that the headcount variable was the one that contributed significantly in terms of information needed for splitting data (also the cut-off headcount level did not change from one run to another). The Gini index also played an important role. Generally, countries with high poverty rates, high Gini index, and that belong to Sub-Saharan Africa (some of the Arab region countries) had very low passthrough rates, while countries with low headcount ratio and low Gini index had higher passthrough rates.

In terms of passthrough by clusters, for all three runs, below are the results of the cluster-specific passthrough rates derived from the training data.

Table A2.1 Cross validation results – PAM

Regions	Run II		Run III	
	Training	Testing	Training	Testing
Arab region	0.38	0.47	0.45	0.31
East Asia and the Pacific	0.82	0.87	0.79	0.70
Europe and Central Asia	0.73	0.74	0.79	0.83
Latin America and the Caribbean	0.53	0.52	0.57	0.57
North America	0.74	0.74	0.74	0.74
South Asia	0.34	0.27	0.34	0.38
Sub-Saharan Africa	0.27	0.27	0.28	0.26

Source: Authors' calculations.

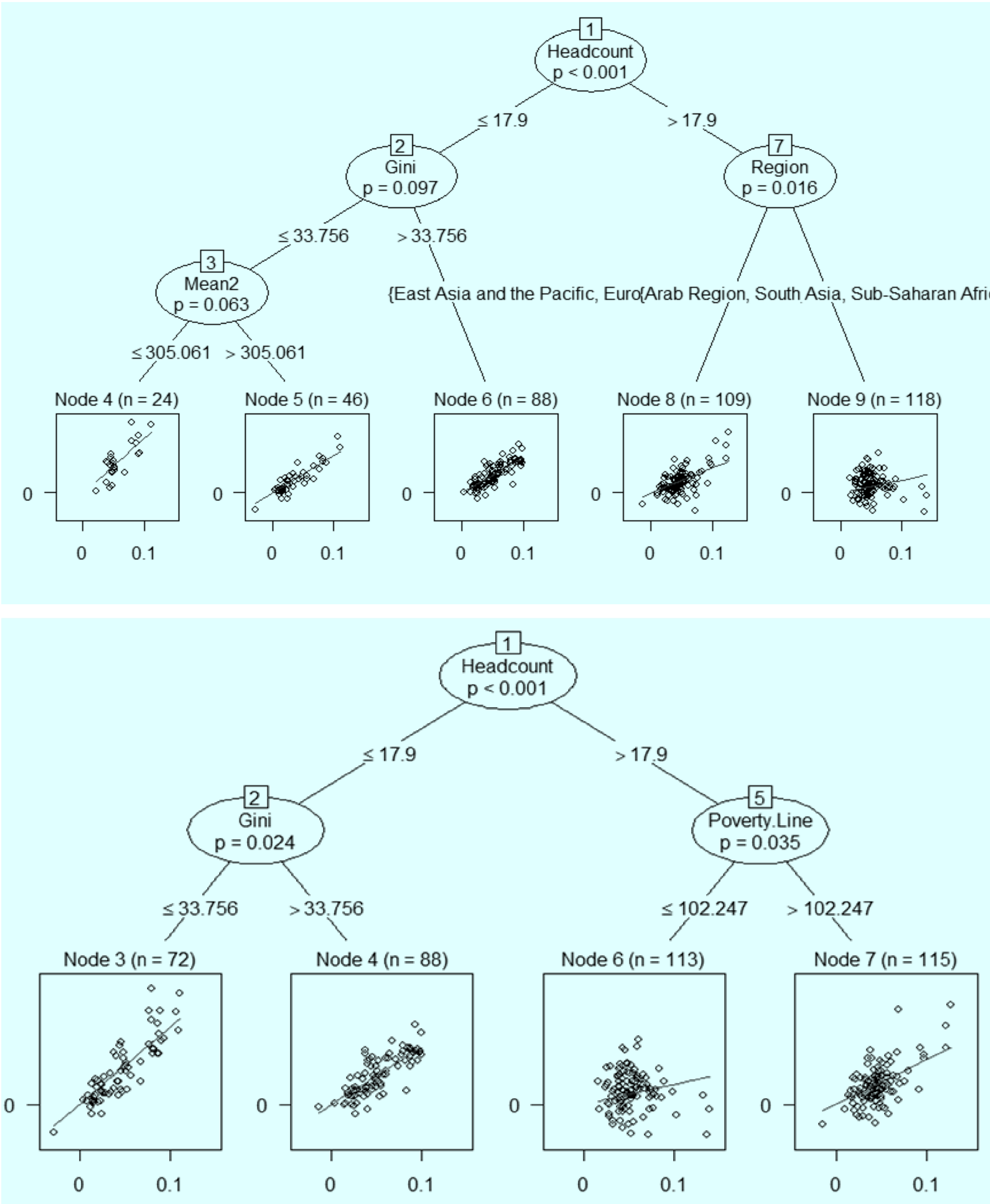
Table A2.2 Cross validation – PAM

Clusters	Run I	Run II	Run III
I	0.30	0.26	0.30
II	0.67	0.58	0.59
III	0.65	0.61	0.63
IV	0.63	0.69	0.74
V	0.79	0.74	0.83

Source: Authors' calculations.

Here as well, cross-validation worked properly. The clustering (PAM) was not as sensitive as with the MOB model: passthrough results for each run were relatively similar. This was also the case when comparing the regional passthrough results from one run to another.

Figure A2.1 Dendogram results for cross-validation



Source: Authors' calculations.

Table A2.3 Cross validation results MOB

Regions	Run II		Run III	
	Training	Testing	Training	Testing
Arab region	0.57	0.53	0.57	0.48
East Asia and the Pacific	0.71	0.69	0.78	0.77
Europe and Central Asia	0.59	0.39	0.62	0.62
Latin America and the Caribbean	0.61	0.69	0.63	0.74
North America	0.69	0.61	0.74	0.63
South Asia	0.65	0.67	0.67	0.35
Sub-Saharan Africa	0.42	0.57	0.37	0.35

Source: Authors' calculations.

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Can the world still reach Sustainable Development Goal (SDG) 1 targets 1.1 and 1.2 by 2030? This question is particularly relevant in light of COVID-19 having derailed many developing economies. Current methods for addressing progress regarding development are limited in that they assume a full transmission of macroeconomic growth forecasts derived from national accounts to household level income captured by surveys. This study offers two contributions. Firstly, it developed a methodology for estimating this passthrough effect using unsupervised clustering methods and reported results at the regional and country levels. Secondly, it used these passthroughs to discount gross domestic product (GDP) growth forecasts available for 183 countries, which were then applied to estimate headcount poverty rates using the extreme poverty line of $1.9 per day and national poverty lines. The results showed that in the best-case full growth passthrough scenario, modest poverty reduction is recorded but the world is still unlikely to reach SDG1 targets 1.1 and 1.2 by 2030. With more realistic scenarios, where modelled growth passthrough results were applied, the poverty forecasts showed only a slight dent from their 2019 baseline. Developing countries, especially poorer countries, should not be concerned solely with policies that enhance GDP growth, but also with its passthrough to household incomes.

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