Policy Research Working Paper 11010

Poverty Projections for Pakistan

Nowcasting and Forecasting

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WORLD BANK GROUP
Poverty and Equity Global Department
December 2024

Policy Research Working Paper 11010

Abstract

In 2019, 21.9 percent of the population in Pakistan lived below the national poverty line. Since then, the COVID-19 pandemic, devastating floods in 2022, and a macro-fiscal crisis with record inflation have profoundly impacted economic activity and income-earning opportunities. The absence of a new household survey limits the ability to ascertain the implications of these different shocks on household welfare and poverty. Up-to-date welfare information is crucial for formulating appropriate policy responses to crises that directly affect households' socioeconomic well-being. To overcome the lack of current data, this paper proposes a microsimulation tool that combines microdata from the latest national household survey with high-frequency macro indicators to produce nowcasts and forecasts of poverty. The tool models household consumption by using individual and household characteristics and accounts for changes in labor markets, inflation, social transfers, and remittances. The results account for household-specific inflation rates, which reflect systematic variation in household consumption patterns and sector-specific growth rates. Using the preferred specification, the findings suggest that in 2024, the poverty rate stood at 25.3 percent, an increase of seven percentage points compared to 2023, with about 13 million additional people falling into poverty. Moreover, in addition to the projected increase in poverty, poor households face disproportionately higher welfare losses and get pushed deeper into poverty.

This paper is a product of the Poverty and Equity Global Department. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at obarriga@worldbank.org.

Poverty Projections for Pakistan: Nowcasting and Forecasting*

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Keywords: poverty, inequality, projections, Pakistan

JEL classification: D31, I31, D60

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1. Introduction

Pakistan has faced various shocks in recent years, including the COVID-19 pandemic, natural disasters, and economic shocks. These shocks are expected to profoundly impact household welfare and poverty rates in the country. Yet, the latest official poverty rates are available for fiscal year 2019 (FY19),[1] the year of the last Household Income and Integrated Survey (HIES). Due to resource constraints and the time it takes to collect and process household survey data, surveys are only implemented every few (2-5) years, undermining data availability. This presents challenges in providing real-time welfare (namely poverty, vulnerability, inequality) analysis and informing the design of policies to mitigate the impact of shocks like economic crises (e.g., price shocks) or natural disasters (such as floods) on people's well-being and their risk to fall into or stay in poverty. To address this issue, policy makers rely on "nowcasting" and "forecasting"[2] poverty rates using aggregate measures of national welfare to estimate poverty incidence levels. This approach is based on the fundamental principle that the incidence of poverty and aggregate measures of national welfare, like GDP per capita, are intertwined.

Our approach explicitly models change in the welfare distribution by using information from sectoral growth and household-specific inflation rates, producing a more nuanced picture of the incidence of poverty and the distributional changes experienced in the country. We model the evolution of labor and non-labor incomes. First, we account for the differential growth trends and concentration of labor across the economy by modeling labor income using information on the growth rates of 11 different sectors. This is key since there are significant variations in sectors' contribution to overall growth, their labor intensity, and the welfare level of individuals employed in different sectors. Second, we include specific conditions to mimic the evolution of non-labor income transfers, with a particular focus on the changes in the real value of the transfers from the main anti-poverty program in the country. Finally, we account for the differential price trends across different good categories and their impact on the effective inflation rate households experience given their consumption basket. We implement this modeling in the case of Pakistan and show how it captures how the differential sectoral growth rates, the loss in purchasing power of public transfers, and the inflation gap between urban and rural areas all together impact the evolution of poverty since the last official measure in FY19 was published. The model is specifically tailored to the conditions of Pakistan, but its methodological approach offers complete flexibility to extend it to other country-specific conditions in terms of relevant economic sectors, non-labor income components, and available inflation information.

Our results are aligned with past evidence on how accounting for the distributional effects of growth produces more accurate predictions of the evolution of poverty (Caruso et al., 2017;

[1] In Pakistan, the fiscal year covers the 12-month period from July to June of the next year. For example, FY19 covers the period from July 2018 to June 2019 inclusive.

[2] Nowcasting refers to the practice of using recently published data to update key economic indicators that are published with a significant lag. Poverty nowcasting relies on actual GDP data, its accuracy depends only on the features of each nowcasting method (reference). Forecasting refers to the practice of predicting what will happen in the future by taking into consideration events in the past and present.

Tateno et al., 2021). We address several limitations of other projection approaches. First, using a single growth rate for household income, usually from the GDP per capita, disregards the fact that total growth is rarely equally distributed across sectors and households. For instance, growth in labor-intensive sectors will have a greater effect on poverty, while, similarly, growth in sectors that employ lower-income individuals is more likely to reduce poverty. Second, not all inflation is created equal, as households across the expenditure distribution have distinct consumption baskets, making differential price trends in food, non-food, and energy create heterogeneous effective inflation rates (Nasir et al., 2023).[3]

We present benchmarking results using an arrangement of forecasting models commonly used in the literature and a detailed description of their modeling and methodological assumptions. We address their limitations by implementing three main variations over traditional forecasting models. First, we use household-level inflation rates to incorporate inflation heterogeneity. Second, we introduce sectoral growth rates and assess the different results using three-sector and eleven-sector models. Third, we independently forecast labor and non-labor income using Pakistan-specific conditions on the evolution of public transfers' purchasing power and household-specific inflation rates. Our results provide an overview of the broader literature on poverty projection and update the poverty estimates for Pakistan during the period of FY20 to FY25 period. This study aims to contribute to the country's ongoing policy discussions on poverty reduction by providing up-to-date poverty estimates and projections.

We find that the projected poverty incidence rates mimic the broader economic upheavals caused by the pandemic, floods, and macroeconomic crises. From a baseline value of 21.9 percent in 2019, poverty is estimated to have increased to as high as 24.9 percent and 25.3 percent at the tail-end of the pandemic and period of high inflation in 2020 and 2023, respectively, with a period of recovery in between. Forecasts predict that, following economic recovery, the poverty headcount will decrease to 18.7 percent by 2025.

The paper proceeds as follows: Section 2 outlines the data and projection methodology, Section 3 discusses the key results and trends, Section 4 compares results to conventional projection methods, and Section 5 concludes.

2. DATA AND METHODOLOGY

2.1 Data

We use both micro and macroeconomic data for the modeling. Microeconomic data provides the baseline levels of poverty and inequality as well as a set of household characteristics. On the other hand, macroeconomic data on sectoral growth and prices are the basis for predicting the evolution of household expenditure and the corresponding welfare changes, including poverty and inequality. The FY19 Household Integrated Economic Survey (HIES 2018/19), conducted by the Pakistan Bureau of Statistics (PBS), provides the expenditure vector to calculate the official

[3] Inflation rates differ systematically across different types of households as their consumption patterns and different types of goods and services have different inflation rates.

poverty rate in the country, being representative at the national, provincial, and urban/rural levels. Across the four provinces, 24,809 households were interviewed, broken down into 15,936 rural and 8,873 urban households.[4] Table 1 shows that the official (national) poverty rate in FY19 was 21.9,[5] but it varied between the provinces and urban and rural areas. The spatial distribution of the poor varies, as the province with the lowest population share (Balochistan) also has the highest poverty rate, almost twice as high as the national poverty rate.

Table 1: Official Poverty rate in Pakistan FY19

	National	Punjab	Sindh	KPK	Balochistan	Urban	Rural
Population (%)	-	53.9	23.0	17.1	5.9	36.4	63.6
Poverty rate	21.9	16.3	24.1	29.5	42.7	10.9	28.1
Share of the poor	-	40.0	25.4	23.0	11.6	18.12	81.9

Source: Author calculations using HIES 2018/19

Note: Population shares use the survey expanded weights

Table 2 provides information on the macroeconomic indicators, including growth rates, inflation, and population. PBS publishes data on population growth rates, inflation, and the GDP series between FY20 to FY22.[6] Growth rates, along with inflation forecasts, between FY23 andFY25 are projected by the World Bank, and published through the semiannual Macro Poverty Outlook.[7] While headline inflation is projected until FY25, Classification of Individual Consumption According to Purpose (COICOP) category-level projections are not available beyond FY23. Additionally, Table 2 showcases one of the main development challenges in Pakistan: The need for substantial growth to outpace population increases. This can be seen in the situation in the FY25, when real GDP growth reached 2.4 percent, but no per capita changes were achieved.

Table 2: GDP and Sectoral Growth Rates, Inflation, and Population

	FY20	FY21	FY22	FY23*	FY24*	FY25*
GDP growth rates, nominal (%)[a]	8.8	16.8	21.1	24.7	32.0	19.7
GDP growth rates, real (%)[a]	-0.9	5.8	6.1	-0.6	1.7	2.4
GDP per capita growth rates, real (%)[a]	-2.6	3.8	4.1	-2.5	-0.6	0.1
Sectoral growth rates, real [a]						
Agriculture	3.9	3.5	4.3	1.0	2.2	2.4
Industrial	-5.7	8.2	6.8	-2.9	1.4	2.3
Services	-1.2	5.9	6.6	-0.5	1.5	2.4
Mining and Quarrying	-7.2	1.7	-7.0	-4.4	0.5	1.0
Manufacturing	-7.8	10.5	10.9	-3.9	1.7	2.6
Electricity Generation and Gas Distribution	3.5	9.0	3.1	6.0	1.4	2.5

[4] The HIES (2018/19) was conducted in the four provinces of Punjab, Sindh, Khyber Pakhtunkhwa (including merged FATA districts), and Balochistan.

[5] The national Cost-of-Basic-Needs (CBN) poverty line in Pakistan was estimated in 2013–14. All poverty estimates provided are based on this official measure of poverty, unless otherwise mentioned. See Appendix A for details.

[6] https://www.pbs.gov.pk/sites/default/files/tables/national_accounts/2021-22/Table_4.pdf

[7] The projections are taken from the Macro Poverty Outlook published in October 2023.

Construction	-3.1	2.4	1.9	-5.5	1.0	1.4
Wholesale & Retail trade	-5.3	10.8	10.3	-4.5	1.1	2.2
Transport, Storage	-8.9	4.9	4.1	-2.9	1.0	1.9
Financial and Insurance Activities	-2.2	5.5	7.2	-3.8	0.0	1.7
Real Estate Activities (OD)	3.8	3.6	3.7	3.7	1.0	2.0
Public Administration and Social Security	3.0	-0.5	1.8	-7.8	1.7	2.6
Other Private Services	5.0	5.1	4.8	5.0	2.2	2.5
Inflation [3][b]	10.7	8.9	12.2	29.2	21.0	13.0
Inflation [COICOP][b]						
Food and Non-Alcoholic Beverages	15.5	13.3	13.4	38.7		
Alcoholic Beverages and Tobacco	21.2	5.6	4.3	65.0		
Clothing and Footwear	9.7	10.1	10.4	18.7		
Housing and utilities	6.9	6.3	10.8	14.1		
Furnishing and HH Equipment Maintenance	10.3	8.4	12.5	31.8		
Health	11.3	8.4	9.4	16.7		
Transport	11.1	1.6	23.9	50.5		
Communication	3.5	0.7	2.4	3.4		
Recreation and Culture	6.4	4.5	8.6	41.6		
Education	5.4	1.3	4.8	9.7		
Restaurants and Hotels	7.3	8.5	12.5	32.4		
Misc.	11.9	11.6	10.6	29.1		
Population (million) [4][a]	227.2	231.4	235.8	240.5	245.2	249.9

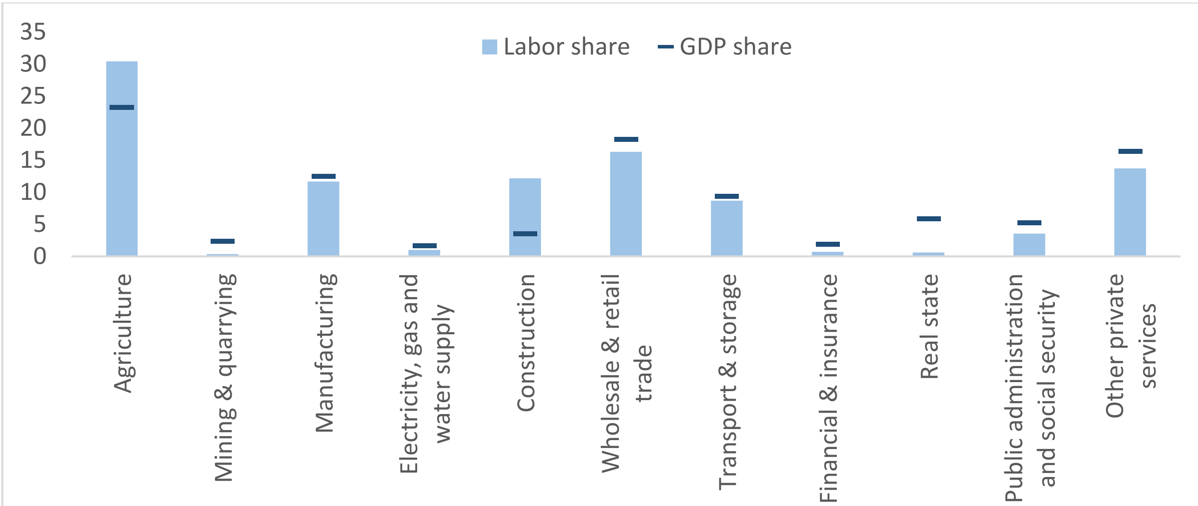
Source: a: Pakistan Bureau of Statistics (PBS) and World Bank (WB), b: Statistical Supplement
Note: COICOP categories aggregate information from 283 expenditure items into 12 main categories

Besides the large heterogeneity in the growth rates across the different sectors of the economy, there is additional variation in terms of the labor intensity of each of these sectors, which does not necessarily match the sector's contribution to the overall GDP. As Panel (a) in Figure 1 shows, while the agriculture sector represents about 23 percent of total GDP in FY19, it absorbs almost 32 percent of the labor force of the total labor force. This implies that expansion in the agriculture sector has the potential to positively impact the welfare of a larger number of households.[8] In addition to economic sectors presenting different levels of labor intensity, workers are not equally distributed across sectors. For instance, individuals working in agriculture are more likely to be at the bottom of the welfare distribution, further reinforcing that which sector expands or contracts produces different welfare implications; see Panel (b) in Figure 1.

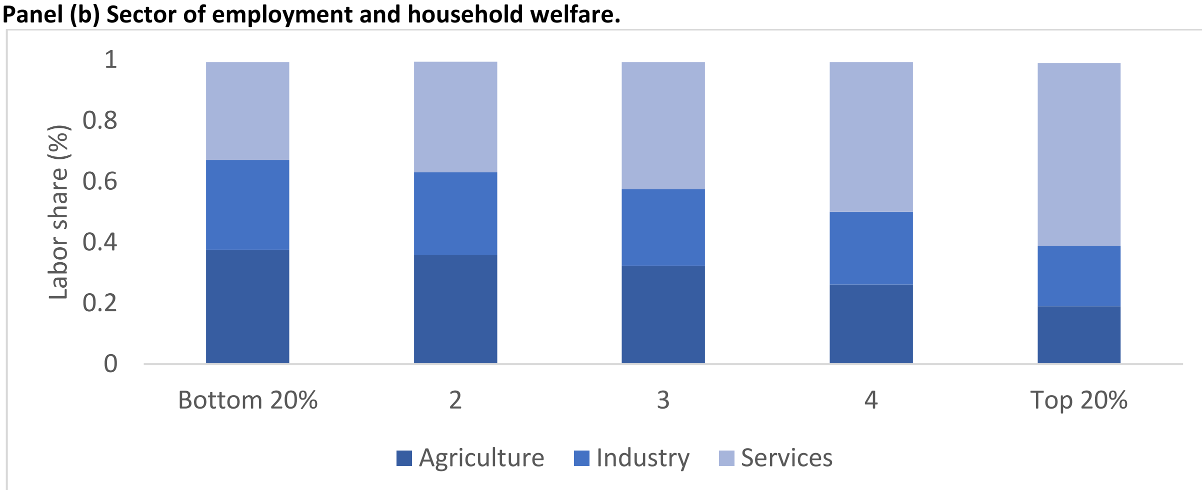
Figure 1: Employment Distribution Across economic sectors

Panel (a) Labor shares and sectoral contributions to GDP.

[8] Subject to market structure and government redistribution of the benefits of growth in other economic sectors.



Panel (b) Sector of employment and household welfare.

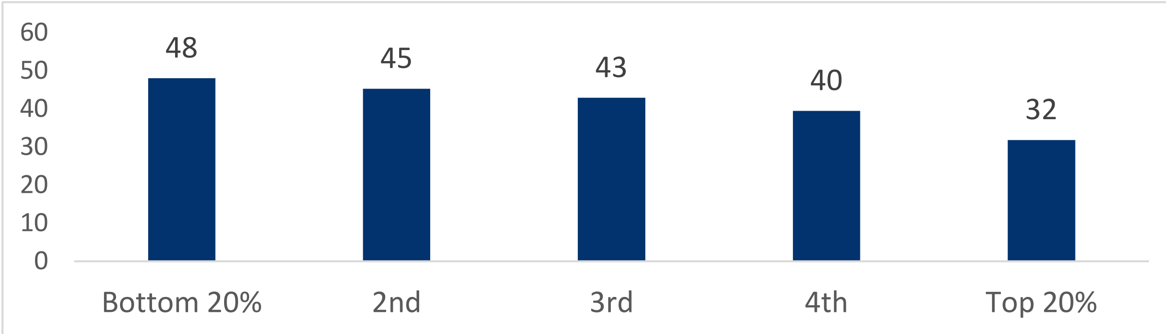


Source: Authors' calculation from HIES 2018/19 data.

Note: (a): Employment sector of the population in the labor force with positive income and compares it with the sector contribution to overall economic activity in FY19 (b) Welfare quintiles use total household expenditure.

As mentioned in the introduction, the Consumer Price Index (CPI) fails to account for inflation heterogeneity arising from differences in price trends and consumption patterns between households with varying income levels. Depending on the price trends across COICOP categories the impact on household welfare will differ depending on their consumption basket. Considering the changes in expenditure shares across the welfare distribution, when food inflation is highest, lower-income households are more negatively impacted, while the opposite occurs when inflationary pressures are caused by raising non-food and energy prices; see Figure 2.

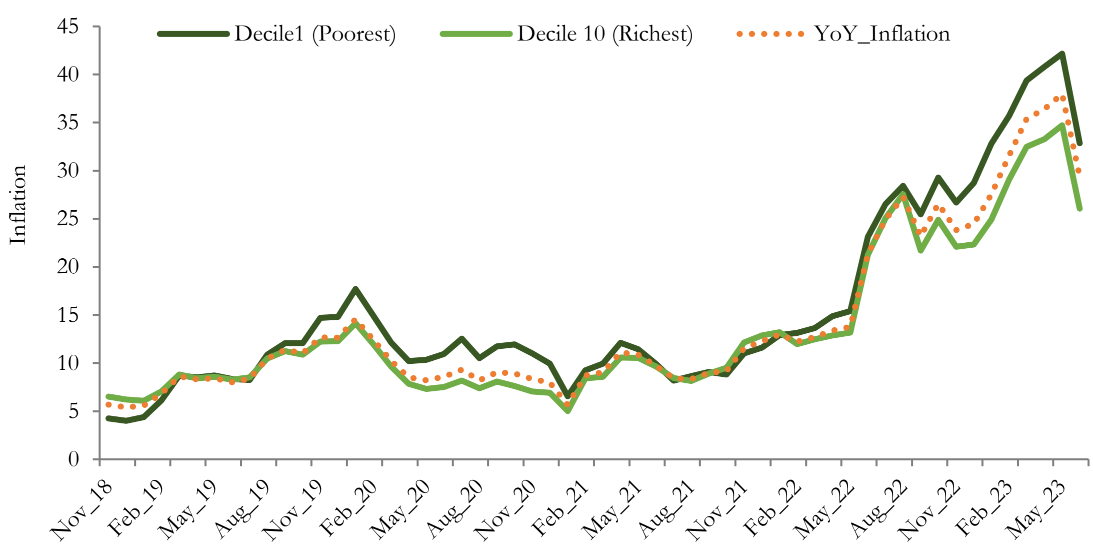
Figure 2. Food expenditure (share)



Source: World Bank using HIES 2018/19 for expenditure shares

In response, we convert total inflation into household-specific inflation rates following Nasir et.al. (2023). The HIES 2018/19 includes information for 283 expenditure items grouped into 12 main categories based on the COICOP classification. We combine expenditures at the COICOP level with their respective inflation rates, as provided by PBS. By aggregating across COICOP categories, we estimate experienced household-specific inflation rates.[9] As Figure 3 shows, depending on the extent to which different COICOP categories experience differential price trends, the perceived inflation by households across the expenditure distribution will differ. For instance, in FY23, households in lower deciles of the expenditure distribution experienced inflation rates that were, on average, one percentage point higher than those experienced by the wealthiest households because of higher food price pressures. Therefore, assuming equal inflation rates across the whole expenditure distribution will potentially underestimate the projected poverty rate.

Figure 3: Inflation Inequality across Income Deciles



[9] Detailed descriptions of the construction of household level inflation rates for Pakistan are provided in Nasir et al. (2023).

Source: World Bank staff calculations based on HIES 2018/19 microdata and PBS inflation data.
Note: Household-specific inflation reflect the different consumption baskets for households across the welfare distribution and the impact of differential price trends between consumption goods have on their effective perceived inflation.

2.2 Methodology

The objective is to project poverty in Pakistan using information from the micro and macroeconomic indicators. For this, we start from the household consumption at baseline in the year 2018/19 (c_0) and implement several steps to compute a new projected expenditure vector ($\hat{c}$) for a household h, as follows(1).

$$\hat{c}_1^h = \frac{c_0^h}{y_1^h} * \left[\sum_{j=1}^{11} \sum_{i=1}^{n} \vartheta * g_j * y_L^{ij} + \left(p_{CPI} * y_{NL}^i\right) + y_{BISP}\right] * \frac{1}{P_1^h} \qquad (1)$$

$$(a) \qquad\qquad (b) \qquad\qquad (c)$$

Where, following (Meyer, Kishwar, & Nasir, 2024),

$P_t^h = \sum_{c=1}^{12} S_{ct}^h * \pi_{ct}$ (2)

With this objective in mind, we implement the following steps:

1. We divide total household income into a labor and non-labor components and model their evolution independently.
2. Total labor income is divided between each employed household member (y_L^i) and assigned the nominal growth rate of the equivalent eleven sectors of the economy g_j^i, with the subscripts i and j denoting the household member and the economic sector, respectively. θ denotes the effective pass-through rate. That is, what percentage of the sectoral growth is transferred into incomes. This implies that a household with a single earner who works in agriculture, will see its labor income growing at the nominal rate of the agriculture sector. On the other hand, a household with two earners working in two different sectors will experience an income growth rate equivalent to the real growth rate of each sector, weighted by the income share of each sector. As indicated by the summation in component (a) of equation (1), we implement the model using the information on the 11 different sectors pointed out in Table 2. The more disaggregated the sectoral information, the more direct the link between sectoral growth and the welfare of the people employed in the sector. For example, this makes it possible to assign differential growth trends for those employed in the transport and public service sectors, which otherwise would have been wrapped under the service umbrella. However, since the model does not include employment transition across sectors,

this higher disaggregation comes at the cost of additional noise.[10] Additionally, disaggregated GDP-growth projections are associated with higher degree of noise and fluctuation. Section 4 compares our specification to alternate models with only three sectors.

3. Non-labor income has two components. The first is the income from BISP transfers (y_{BISP}). The value of the cash transfers made under BISP's flagship UCT program has gradually increased over time in nominal terms. We use the yearly change in the nominal value of payouts (as announced by BISP) to simulate the evolution of households' income from public transfers, using the reported values in HIES 2018/19 as a base.[11] The second component includes other non-labor incomes such as pensions and private transfers (y_{NL}). For simplicity, we model its evolution by using the headline CPI. While the model is highly flexible, and additional components of non-labor income can be independently modeled to simulate their net impact on poverty under different scenarios (see component (b) in equation (1)), data availability limits the level of heterogeneity that we can model.
4. To capture the impact of differential price trends across 12 COICOP components, we estimate a household-specific inflation rate (Meyer, Kishwar, & Nasir, 2024). As shown in equation (1) and (2) P_1^h denotes the household-specific inflation rate between the baseline period $t = 0$ and the year we project to $t = 1$. As noted in the previous section, differential price trends affect households' effective inflation rates depending on the composition of their consumption basket.
5. Finally, we use the propensity to consume of each household $\left(\frac{c_0}{y_0}\right)$ at baseline to transform the predicted household income into household expenditure at $t = 1$, which is the measure to estimate the incidence of poverty using the official and international poverty lines.

The heterogeneity of household income growth is crucial to properly model its evolution over time. Our method introduces several characteristics that allow us to reflect this heterogeneity. First, we account for the significant variation in the growth rates across sectors by using information from eleven different sectors, which greatly differ in the growth trend, demand for labor, and initial welfare levels of their workforce (see details panels (a) and (b) in Figure 1). A second source of income growth heterogeneity comes from the modeling of non-labor income. BISPS transfers are not indexed to inflation, making them lose purchasing power over time.[12] This means that households with the same amount of non-labor income at baseline will have different projected expenditure levels depending on the composition of their non-labor income. Finally,

[10] We model the evolution of labor income using the growth of real GDP per capita when a person with positive labor income has no sector identified; this represents 0.75% of the population with positive labor income.

[11] The quarterly payment under BISP's UCT program was Rs. 5,000 in FY19. This was increased to Rs. 6,000 effective February 1, 2020, to Rs. 6,500 effective February 1, 2022, and to Rs. 7,000 effective March 1, 2022. Finally, it was increased by 25 percent effective January 1, 2023, to reach Rs. 8,750 per quarter.

[12] In 2018/19 about 8 percent of the households received BISP transfers, and 92 percent had some type of non-labor income.

we use household-specific inflation rates to account for the impact of differential price trends and household consumption baskets.

2.3 Key Assumptions and Limitations

The simulation approach depends on certain key assumptions on the underlying income generation process of household, labor markets, and their propensity to consume.

The first assumption is that individual labor incomes grow at the nominal rate of the employment sector, implying that there is a full passthrough to workers via wages. The effective passthrough, ϑ, rate is period-dependent as it is the result of the composition of the economy and the capacity of workers to adjust their wages, with evidence suggesting countries with large informal sectors and high inequality present lower passthrough rates as economic growth is more likely to be captured by wealthier, and non-poor, deciles (Tateno et.al., 2021).[13] We assume a passthrough rate of one ($\vartheta = 1$) since labor income is modeled independently and not directly transformed into consumption. Changes in this assumption will attenuate the impact of sectoral growth on poverty, but only with a small net impact.

The second modeling assumption is also related to labor markets and implies that individual workers remain in their respective employment sectors, with only wages adjusting in the direction of sectoral growth. Furthermore, we assume no shifts in the level of unemployment in response to crises and lower growth/constant sector-level labor share. While both these assumptions stem from data limitations, as the lack of a labor panel implies we cannot test for sectoral transitions, we believe that adjusting for these dynamics would not be associated with a substantial shift in our projections. As highlighted in Appendix Figure B1, the labor force participation across demographic and spatial groups (Panels E-F), as well as the distribution across sectors and by employment type (Panels A-D), has been stable over the years. This is likely linked to a highly degree of informality which absorbs shocks to the labor market and allows for relatively fast adjustment of wages in the short to medium run (Loayza & Rigolini, 2006). Consequently, while important, these dynamics are unlikely to strongly impact short-term projections in a context like Pakistan.

Third, we assume there are no changes in the composition of households. That is, we keep the HIES 2018/19 sampling weights constant across the period, not allowing for population growth, the labor force, or changes in the territorial distribution of households.[14] This is a strong assumption, yet the results appear to be robust.

[13] In Pakistan, a passthrough often used 0.86 as the consumption share is around 86 percent in total GDP.

[14] We implemented several tests to update the 2018/19 sampling weights to reflect the information on population size and distribution from latest population census. All of our results were robust to these changes.

Lastly, the model does not make any adjustment to the consumption-income ratio for households, assumed to be constant. Future iterations of the model will seek to incorporate its variability to allow for more specificity in our projections.

There are additional assumptions associated with the calculation of household-specific inflation, detailed in (Meyer, Kishwar, & Nasir, 2024). Summarily:

The calculation assumes that the composition of consumption baskets, and hence the COICP category weights, remained constant over time and across changes in income levels (zero elasticity). Related to this, to allow a reasonable degree of replicability and comparability across time and contexts, consumption baskets are not disaggregated beyond the base 12 categories.

Additionally, the calculation does not differentiate between purchased and home-produced consumption items, which can be especially important when considering differences across crop-producing or urban areas. This is certainly a limitation, but future iterations and work on disaggregating inflation impacts will seek to model this nuance explicitly in the estimation strategy.

Lastly, household-specific inflation can only be employed in the nowcasting (up to FY23). For forecasts for FY24 and FY25, we are restricted to using headline inflation; that is, $P^h = P$ for these years. This is due to the unavailability of consumption category-specific inflation rates for years beyond FY23.

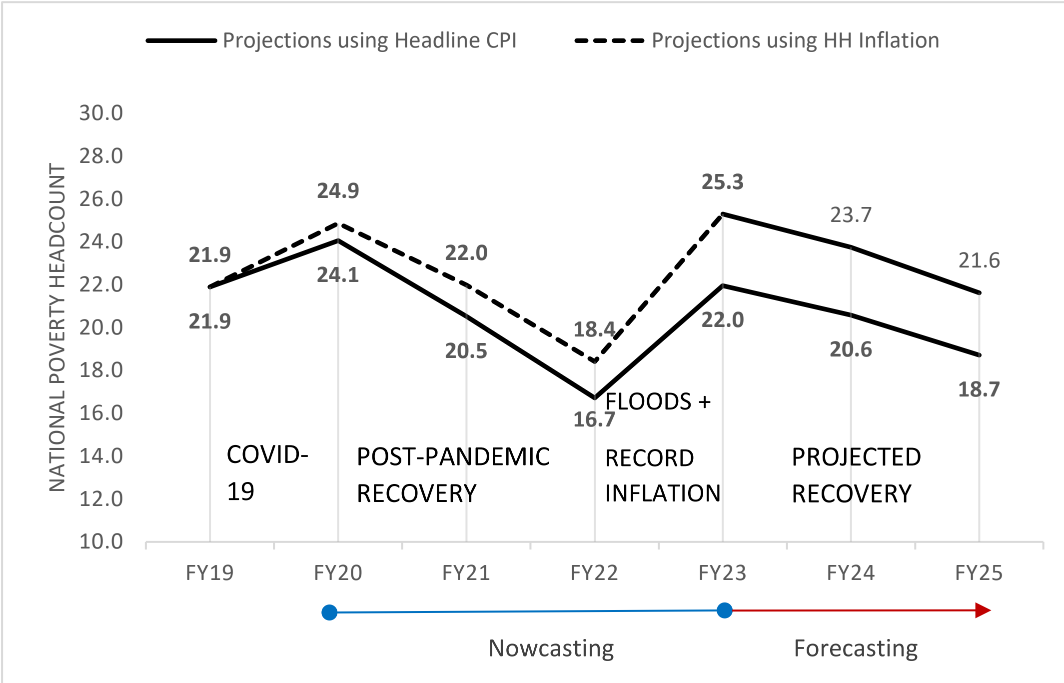
It is essential to recognize that the base specification preferred in this paper provides a starting point for a micro-macro projection model, with significant additional flexibility available to adjust and further enrich the set-up to address specific policy questions.

3. RESULTS

Using our preferred specification, we both nowcast and forecast poverty rates till FY25. While both processes are similar in principle, the data availability for nowcasted and forecasted results may often differ due to the unavailability of input information for future years. In this context, while it is important to distinguish between the two methodologically, it remains valuable to consider the interpretation of results and their policy implications jointly.

Our nowcasted results cover the period from the baseline in FY19 to FY23. Figure 4 presents the projected evolution of poverty, exhibiting specific trends that mimic the shocks and recovery of the Pakistan economy. From 21.9 percent in FY19, poverty increased to 24.6 during the COVID-19 crisis. After the main impacts of the COVID-19 pandemic passed, the country saw a post-pandemic recovery where poverty went down consecutively for two years, reaching 17.1 in FY22. However, at the start of FY23, the combination of devastating floods that destroyed infrastructure and reduced agricultural output, together with record inflation levels and economic crisis, poverty increased again.

Figure 4: Poverty projections
Official poverty line



Source: Authors' calculation from HIES (2018/19) data.
Note: Projections use preferred specifications following equation (1), including information from real growth from eleven economic sectors to model labor income. *Projections using Headline CPI* (solid line) use headline CPI for the whole series. *Projections using HH inflation* (dashed line) are based on household-specific inflation, as described in the methodological section, until FY23. However, due to the lack of disaggregated inflation projections post-FY23, later poverty projections are deflated using expected headline inflation.

The household-level poverty rate from FY23 to FY25 is forecasted using headline CPI instead of COICOP-disaggregated inflation. These indicate the possibility of an economic recovery in later years, which is projected to bring poverty back to its initial level, marking a period of five years without additional poverty gains.

Figure 4 also shows that using an aggregate measure of inflation (headline CPI) underestimates the projections of poverty rates compared to using disaggregated COICOP-level data on inflation (subject to availability). As indicated by the dashed line for FY19 to FY23, accounting for differential price trends and consumption baskets when projecting inflation, produces poverty rates that are consistently higher than those based on average national inflation. This is because the approach does not capture how lower-income households and those close to the poverty line whose food consumption is a large share of the total consumption basket, likely experienced higher inflation rates than the national average. This is important given that higher food prices mostly drove inflationary pressures.

Ignoring inflation heterogeneity across income groups results in an underestimation of poverty rates. Similar results are found for income inequality. The comparison between inequality (Gini coefficients) obtained by average and household-level inflation reveals that the latter is consistently higher. Overall, these findings emphasize the importance of considering the distributional effects of inflation when projecting poverty and inequality to obtain more accurate estimates that account for differences in consumption patterns and price trends across households.

The flexibility of our modeling approach allows us to make subnational-level predictions that account for each region's economic structure in terms of share of urban population, sector of employment, and access to public and private transfers. Table 3 presents the evolution of poverty rates for each of the country's four provinces and urban and rural settings. The evolution of poverty rates across regions follows the overall trends at the national level. However, by FY23, KPK and Baluchistan are predicted to have about 3 percentage points higher poverty rates than those at the beginning of the period. At the same time, Punjab and Sindh lost all the past progress in poverty reduction during the same period. Considering that urban households are more likely to rely on sectors with more pronounced contractions (manufacturing and services), it is not surprising that between FY22 and FY23, they experience a larger increase in poverty (54 percent) vis-à-vis rural areas (26 percent).

Table 3: Poverty projections at provincial and urban/rural level

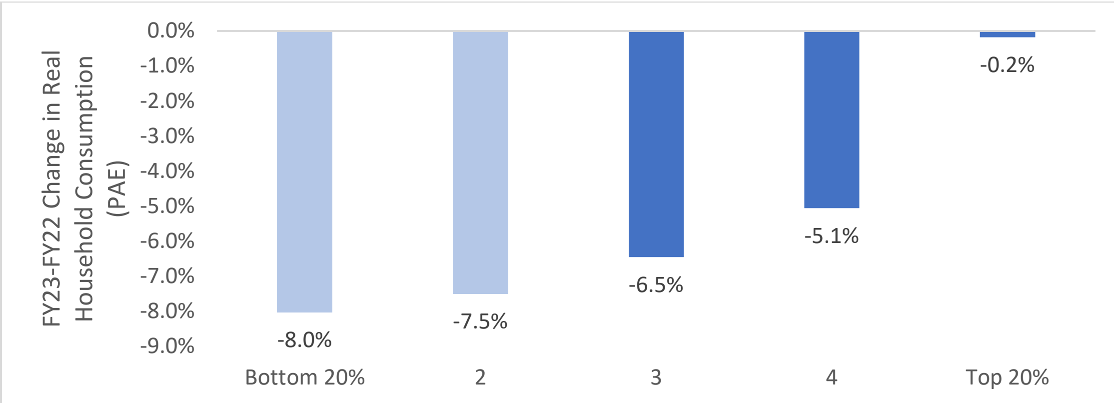
	FY19	FY20	FY21	FY22	FY23	FY24	FY25
Punjab	16.3	19.1	15.5	11.8	15.9	14.7	13.3
Sindh	24.1	26.0	21.9	18.4	24.0	22.1	20.0
KPK	29.5	32.3	29.3	25.4	31.5	30.3	27.8
Balochistan	42.7	46.7	40.8	36.7	45.9	43.4	39.7
Urban	10.9	13.4	11.1	8.1	12.6	12.5	11.3
Rural	28.2	31.0	26.4	22.2	27.8	25.5	23.2

Source: Authors' calculation from HIES 2018/19 data.

Note: Preferred specification uses household-specific inflation as described in the methodological section until FY23. Due to the lack of disaggregated inflation projections, past FY23 projections have been deflated using headline inflation.

An advantage of a non-distributionally neutral model is that it provides information on which individuals will be most affected during a crisis. Given the modeling process, this is intrinsically linked to the evolution of sectoral growth and the initial distribution of households of different welfare levels across sectors. For reference, we present the changes in welfare levels across the expenditure distribution between FY22 andFY23. Figure 5 shows that while there is a reduction in expenditure for households across all quintiles, the highest losses occur for those at the bottom 40 percent.

Figure 5: Welfare impacts of economic contraction FY22-FY23



Source: Authors' calculation from HIES 2018/19 data.
Note: Projections use preferred specification following equation (1), including information from nominal growth from eleven economic sectors to model labor income and headline inflation.

4. ROBUSTNESS CHECKS

Our modeling assumptions are generally aligned with the overall forecasting/nowcasting literature. Alternative methods are broadly divided into distributionally neutral (poverty growth elasticity, neutral distribution growth) and non-distributionally neutral, where heterogenous growth rates across households introduce changes in the welfare distribution (quintile growth contribution, sectoral growth models). A detailed description of each method is provided in Appendix A. Poverty-growth elasticity (PGE) uses the ratio between the percent change in the poverty headcount and the percent change in real per capita GDP to project poverty. Evidence shows that the value of the PGE is dependent on the period used. Meanwhile, the neutral distribution method (NDG) uses the growth in real per capita consumption (with a pass-through) and applies it to every household. These methods keep inequality constant as they only shift the welfare distribution to the right (left) as positive (negative) growth occurs.

Non-neutral distribution methods use additional information to model changes in the welfare distribution. Quintile growth contribution (QGC) models build on the NDG approach but allow different income distribution quintiles to grow at different rates. For this, total growth equals the real GDP per capita, but it is distributed across the initial welfare quintiles, weighting it by their past contribution to growth, as informed by the previous Growth Incidence Curve (GIC). Finally, sectoral models recognize that GDP per capita growth differs across sectors of the economy and, therefore, does not translate into similar income growth rates across the income distribution. For instance, GDP growth led by labor-intensive sectors will have a more considerable impact on household welfare than economic growth prompted by sectors intensive on capital. Usual modeling approaches use the employment sector of the household member with the highest income and apply the growth rate of the three main economic sectors (agriculture, manufacturing, services) or more disaggregated data, such as eleven-sector models.

While not explicitly stated, these methods include underlying assumptions on the constant distribution of labor across sectors and no relative wage changes. Moreover, the formulation of these models does not lend itself to modeling specific country-specific conditions in households' income-generating functions, such as changes in remittance flows or social transfers.

We compare the nowcasted and forecasted poverty rates obtained through different methods incorporating headline inflation. Table 4 presents the results for a range of models: PGE,[15] NGD, and NGD with a pass-through rate of 0.86, QGC, and sectoral models. Overall, we observe that, regardless of the method used, the poverty rate increases for FY20, attributed to lower growth caused by COVID-19. Thereafter, poverty consistently declines until FY23, when this trend is reversed. For FY24 and FY25, the last two years forecasted, poverty goes down following the projected economic recovery. The poverty levels in FY25 differ across methods as they accumulate differences across the years, meaning that the size of the prediction divergence increases with the length of the time used.

Table 4: Comparison of Projected Poverty Estimates through Different Methods

Methods	FY19	FY20	FY21	FY22	FY23	FY24	FY25
Preferred specification: equation (1)		24.6	20.8	17.1	22.2	20.8	18.9
Poverty Growth Elasticity		22.5	21.6	20.7	21.2	21.3	21.3
Neutral distribution (0.86 passthrough)		24.3	20.7	16.8	20.5	16.0	13.9
Democratic	21.9	23.9	20.9	17.8	19.9	20.3	20.1
Plutocratic		24.1	21.0	17.9	19.80	20.2	20.2
3-Sectors		24.7	20.8	16.7	21.2	17.6	15.7
11-Sectors		25.0	20.5	16.2	22.8	20.8	18.8

Source: Authors' estimations based on HIES 2018/19

Note: Results from FY20 onwards are projections. Preferred specification follows equation (1), including information from nominal growth from eleven economic sectors to model labor income and household-specific inflation as described in the methodological section until FY23. Due to the lack of disaggregated inflation projections, past FY23 projections have been deflated using headline inflation. All other projections rely on headline inflation and nominal growth rates. All models have the total household expenditure vector except for the preferred specification. Growth and poverty changes between FY16 and FY19 are used to estimate the elasticity for the Poverty Growth Elasticity and the Growth Incidence Curve for the Quintile growth contribution. Estimate poverty growth elasticity for real GDP per capita and official poverty rate between FY16 and FY19 is -1.06. The neutral distribution model uses a passthrough of 0.86 to reflect the consumption share on total GDP; results using higher (lower) passthrough rates present marginally more (less) pronounced variations of poverty to growth. Quintile growth contribution projections include a Democratic approach, where households within a quantile receive the same per-capita income amount, and a Plutocratic Approach, where each household receives an income based on its share in the total income within its quantile. Projections using sector-level growth rely on the sector of employment of the member with the highest reported labor income.

To assess the accuracy of these methods, we conducted a back-casting exercise for poverty rates spanning from FY18 to FY12. Among the methods employed, our preferred specification is competitive in predicting poverty rates in FY16 and FY14, presenting point estimates that are

[15] The measure of elasticity is based on the international poverty line.

close to the observed poverty levels. Moreover, our preferred specification allows for much in-depth distributional analysis by incorporating the evolution of labor and non-labor income components. While a three-sector model also provides competitive estimates, it is evident that expanding the set of sectors allows for a more comprehensive distributional analysis. This is desirable despite the added noise, as our focus is on the accuracy of the estimates rather than the precision. For FY12, the prediction accuracy of models goes down, which is an expected outcome for predictions further into the past.[16]

Table 5: Comparison between Observed and Backcasted Poverty

Method	FY16	FY14	FY12
Official Poverty	24.3	29.5	36.3
Preferred specification: equation (1)	28.8	31.4	30.7
Poverty Growth Elasticity	24.0	25.5	26.8
Neutral distribution (0.86 passthrough)	29.6	32.4	31.6
Democratic	29.6	34.8	39.6
Plutocratic	29.7	35.0	39.7
3-Sectors	28.7	31.2	29.8
11-Sectors	28.8	31.4	30.7

Source: Authors' estimations based on HIES 2018/19 and the Household Integrated Income and Consumption Survey (HIICS) 2015/16.

Note: Preferred specification follows equation (1), including information from nominal growth from eleven economic sectors to model labor income and household-specific inflation as described in the methodology. All other projections rely on headline inflation and nominal growth rates. Growth and poverty changes between FY16 and FY19 are used to estimate the elasticity for the Poverty Growth Elasticity and the Growth Incidence Curve for the Quintile growth contribution. Estimate poverty growth elasticity for real GDP per capita and poverty between FY16 and FY19 is -1.06. The neutral distribution model uses a passthrough of 0.86 to reflect the consumption share on total GDP; results using higher (lower) passthrough rates present marginally more (less) pronounced variations of poverty to growth. Quintile growth contribution projections include a Democratic approach, where households within a quantile receive the same per-capita income amount, and a Plutocratic Approach, where each household receives an amount of income based on its share in the total income within its quantile. Projections using sector-level growth rely on the sector of employment of the member with the highest reported labor income.

5. CONCLUSION

Since 2019, the last year when data to estimate poverty and inequality levels were available, Pakistan has experienced large macroeconomic and natural shocks. However, the absence of new household survey information limits the ability to assess the implications of the different shocks on household welfare to formulate appropriate policy responses.

[16] Slight deviations from the observed poverty rates are introduced by changes in the sampling frameworks due to urban households being oversampled in HIICS 2015/16 and the inclusion of the Federally Administered Tribal Areas (FATA) within the Khyber Pakhtunkhwa province. FATA areas are affected by violence and economically disadvantaged when compared with the rest of the country. We implement additional reweighting tests with no qualitative change in the results.

Our projections on poverty rates, using a microsimulation tool explicitly tailored to the dynamics of Pakistani households' labor and non-labor income flows, show that poverty in 2023 stands at about four percentage points above its 2019 level. This result represents a break with the trend of continuous poverty reduction in the past decade. It hides heterogeneous impacts across different population groups, particularly those more reliant on labor income from the manufacturing sector and those more exposed to the detrimental effects of rapidly increasing food prices.

Our results are quantitatively competitive against commonly used poverty projection alternatives, with the advantage of allowing for distributional analysis. When comparing our model with off-the-shelf alternatives, we identify two main advantages. First, we allow for non-distributionally neutral changes in welfare distribution, an important factor considering that welfare impacts in households correlate with their initial characteristics in terms of location, labor supply, and consumption patterns. Second, we tailor the model to the characteristics of the social transfer programs in Pakistan, which implies greater modeling flexibility and the opportunity to simulate different policy interventions.

The analysis and projections developed in the paper showcase how using various economic data sources can be useful to assess the current situation in the absence of current data. The results highlight the vulnerability to falling into poverty or destitution that Pakistani households face when confronted with shocks. The analysis also highlights that labor income has been the main driver for poverty reduction, resulting from people moving to better-paid employment opportunities during normal times. It also shows that when shocks occurred, informality increased (and served as a cushion to prevent unemployment), indicating that informal employment helped people stay economically engaged, albeit in low-productivity, low-wage activities.

The base model presented provides a foundation on which future work could iterate and improve, especially in modeling its inputs subject to policy-specific questions and data availability across different contexts. A better understanding of how labor market dynamics play a role in people's socioeconomic well-being will allow for improvements in the model presented in this paper and ultimately help inform policy.

REFERENCES

Aguilar, R. A. C., Mahler, D. G., & Newhouse, D. (2019). Nowcasting global poverty. *IARIW-World Bank*.

Bhalla, S., Bhasin, K., & Virmani, A. (2022). Pandemic, poverty, and inequality: Evidence from india.

Blumenstock, J., Cadamuro, G., & On, R. (2015). Predicting poverty and wealth from mobile phone metadata. *Science, 350*(6264), 1073-1076.

Bourguignon, F. (2003). The growth elasticity of poverty reduction: explaining heterogeneity across countries and time periods. *Inequality growth: Theory policy implications, 1*(1).

Caruso, G. D., Lucchetti, L., Malasquez, E. A., Scot, T., & Castaneda, R. (2017). But? what is the poverty rate today? testing poverty nowcasting methods in Latin America and the Caribbean.

Datt, G., & Ravallion, M. (1992). Growth and redistribution components of changes in poverty measures: A decomposition with applications to Brazil and India in the 1980s. *Journal of development economics, 38*(2), 275-295.

Dercon, S., & Lea, N. (2012). The prospects of the poor: The future geography of poverty and its implications for DFID.

IMF. (2022). *Fiscal Policy from Pandemic to War: Online Annex 1.1. Poverty Projections using Growth Forecasts*.

Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., & Ermon, S. J. S. (2016). Combining satellite imagery and machine learning to predict poverty. *353*(6301), 790-794.

Karver, J., Kenny, C., & Sumner, A. (2012). MDGs 2.0: What goals, targets, and timeframe? *IDS Working Papers, 2012*(398), 1-57.

Lanjouw, P., Chen, S., & Kraay, A. (2013). The World Bank's Poverty Target of 3% in 2030. Assessing the Realism of this Goal and Exploring Some Country-Level Implications. *World Bank, Washington, DC. Mimeo*.

Leventi, C., Navicke, J., Rastrigina, O., Sutherland, H., Ozdemir, E., & Ward, T. (2013). *Nowcasting: estimating developments in the risk of poverty and income distribution in 2012 and 2013*. Retrieved from

Mahler, D. G., Nishant Yonzan, Christopher Lakner, R. Andres Castaneda Aguilar, and Haoyu Wu. (2020). Projecting global extreme poverty up to 2030: How close are we to World Bank's 3% goal?

Misselhorn, M., & Klasen, S. (2006). Determinants of the growth semi-elasticity of poverty reduction.

Newhouse, D. L., & Vyas, P. (2018). *Nowcasting poverty in India for 2014-15: A survey to survey imputation approach*. Retrieved from

Nishant, Y., Christoph, L., & Daniel, G. M. (2020). Projecting global extreme poverty up to 2030: How close are we to World Bank's 3% goal?

Olivieri, S., Radyakin, S., Kolenikov, S., Lokshin, M., Narayan, A., & Sanchez-Paramo, C. (2014). *Simulating Distributional Impacts of Macro-dynamics: Theory and Practical Applications*: World Bank Publications.

Rastrigina, O., Leventi, C., & Sutherland, H. (2015). *Nowcasting: estimating developments in the risk of poverty and income distribution in 2013 and 2014*. Retrieved from

Ravallion, M. (2013). How long will it take to lift one billion people out of poverty? *The World Bank Research Observer, 28*(2), 139-158.

Ravallion, M., & Chen, S. (2012). Monitoring Inequality.

Tateno, Y., & Zoundi, Z. (2021). Estimating the short-term impact of the COVID-19 pandemic on poverty in Asia-Pacific LDCs. In: Issue March.

Yoshida, N., Uematsu, H., & Sobrado, C. E. (2014). Is extreme poverty going to end? An analytical framework to evaluate progress in ending extreme poverty. *World Bank Policy Research Working Paper*(6740).

APPENDIX A: Additional Information on Poverty Measurement and Projections

Poverty Measurement in Pakistan

Poverty measurement in Pakistan is based on data from the Household Integrated Economic Survey (HIES). There are nine waves of comparable HIES survey rounds currently available between 2001 and 2018. The HIES 2018/19 was the first survey to use a new sampling frame based on the Housing and Population Census 2017, and to include the newly merged areas in Khyber Pakhtunkhwa (KPK), previously known as the Federally Administered Tribal Areas (FATA).

The World Bank uses two separate measures of monetary poverty. First, the Planning Commission and the Pakistan Bureau of Statistics (PBS) have developed a poverty line specific to Pakistan for official poverty measurement. This is used to inform policy design and discourse at the national level. Second, the World Bank uses the international poverty line for global poverty monitoring, currently expressed in 2017 PPP US$.

Official Poverty: In Pakistan, the welfare metric used to estimate poverty is consumption per adult equivalent, spatially deflated to account for price differences across regions. The food poverty line reflects the cost of consuming 2,350 calories per adult equivalent per day, and a total poverty line is estimated to reflect the expenditure necessary to satisfy non-food needs. The Cost-of-Basic-Needs (CBN) poverty line estimated in 2014 was set at PKR 3,030 per adult equivalent per month (or PKR 6,669 in 2023 prices). All estimates provided in this note are based on the official measure of poverty, unless otherwise mentioned.

International Poverty: For international poverty measurement and cross-country comparisons, the welfare metric used is consumption per capita, adjusted to 2017 PPP US$. There are three poverty lines currently in use: (i) the *International Poverty Line* of US$2.15 a day, which defines the extreme poverty rate; (ii) the *Lower Middle-Income Class Poverty Line* of US$3.65 a day; and (iii) the *Upper Middle-Income Class Poverty Line* of US$6.85 (each expressed in 2017 PPP). Table A1 compares poverty projections estimated by the different methodologies using the International Poverty Line.

Poverty Projection Methodologies

Poverty-growth elasticity (PGE)

This method has often been used by the World Bank for forecasting poverty. The accuracy of this approach depends upon the accuracy of predicted growth and elasticities (Aguilar et al., 2019; Tateno & Zoundi, 2021). The PGE is the ratio between the percent change in the poverty headcount and the percent change in real per capita GDP. The poverty is projected based on PGE by using the following formula:

$$H_{1,PGE} = \left(1 + \eta_{H/g} \cdot g\right) \cdot H_0$$

with H_t Poverty Incidence, $\eta_{H/g}$ Growth Elasticity of Poverty, g Real Growth of GDP per capita. This approach incorporates both the growth and the inequality components (Datt & Ravallion, 1992).

Future poverty is frequently predicted using a semi-growth elasticity or constant growth elasticity assumption. Semi-growth elasticity, according to Misselhorn and Klasen (2006), is more helpful for policymakers who typically concentrate on the percentage point reduction of the poverty rate. These methods can be effective for projecting poverty in a cross-country setting, as demonstrated by Bourguignon (2003) and Misselhorn and Klasen (2006). Dercon and Lea (2012) projected global poverty rates using the constant semi-growth elasticity approach. However, it is problematic to estimate poverty rates for the far future when using either constant semi-growth elasticity or constant growth elasticity (Yoshida et al., 2014).[17] Some authors (Karver et al., 2012; Lanjouw et al., 2013; Nishant et al., 2020) adopted a "distribution-neutral approach" as a result of the issues with the constant (semi-) growth elasticity approach.

Neutral distribution method (NDG)

This approach rests on the assumption that the growth in real per capita consumption of all the households is identically affected by GDP per capita growth and there is full knowledge of the pass-through ϑ. If ϑ is the pass-through of GDP per capita to survey household consumption expenditures, the poverty estimates are derived from:

$$y_{1,\,i} = (1 + \vartheta g) y_{0,i}$$

where $y_{0,\,i}$, presents incomes at time period t, $y_{1,\,i}$ is individual incomes at time period t+1, g is real GDP growth rate in future time periods. The validity of poverty estimate using the NDG approach depends on the quality of GDP data and population estimates, the level of similarity of income growth across households (the more similar the growth are, the more accurate is the poverty estimate), and the level of knowledge about the passthrough (Caruso et al., 2017).

This approach has the advantage over PGE as it does not rely on any historical information and may use different poverty lines to calculate poverty rates. This approach can forecast the real poverty rate even in the case of expected increases in income or consumption for any given level of inequality. Since this method uses the actual distribution of income or consumption, poverty rates accurately reflect the curvature of the distribution of income or consumption. In other words, it only shifts that distribution. As a result, in contrast to the constant growth or semi-growth elasticity approach, this method can predict poverty rates as long as inequality does not

[17] As described in Yoshida et al. (2014), “Income distribution is not flat and often shows a large concentration of population in the middle-income group. When the poverty rate is very high, a poverty line is often located in the huge population mass. As a result, even a small improvement in income can lift many out of poverty. However, as the poverty rate continues to decrease, not many are located near the poverty lines; as a result, a small increase in income can lift only a few out of poverty. Therefore, semi-growth elasticity tends to decline as the poverty rate declines.”

change. This approach presumes no changes in inequality, which in reality has been changing over time as demonstrated by Ravallion (2013) and Ravallion and Chen (2012). Hence, the assumption of constant inequality could lead to inconsistent estimates and, therefore, is considered the main drawback of this approach. In response to these limitations, different authors (Caruso et al., 2017; Tateno & Zoundi, 2021) use the quintile growth contribution method, which is a generalized form of the NDG approach.

Quintile growth contribution (QGC)

The QGC approach expands the NDG approach and allows for different quintiles of the income distribution to grow at different rates, while the NDG assumes that all households (i.e., different quintiles) grow at the same rate. Each quintile's growth is dependent on how much it contributes to overall growth over a period of known data. This approach uses the Growth Incidence Curve (GIC) for previous periods, whereby the use of historical episodes implies that the economy operates as it did in the past in terms of how much each quintile participates in the growth process. GICs provide information about the income gains or losses experienced by the typical household within each percentile of the income distribution. According to Olivieri et al. (2014) even among households with very similar initial per capita household income levels, GICs can hide a sizable amount of heterogeneity in the absolute size of impacts. Under QGC, there are two methods to project poverty: (1) Democratic (2) Plutocratic. The former approach treats households within the same quintile similar whereas the latter considers relative differences between households within the same quantile as discussed below.

Democratic Approach

This approach underlines the assumption that households within the same quintile are similar. All households within a quantile receive the same per-capita income amount:

$$y_{1,i}^{demo} = y_{0,i,q} + \frac{\Delta \hat{y}_q}{n_q} = y_{0,i,q} + \Delta y_{q,\,i}$$

where $y_{0,\,i}$ is individual incomes at time t, $y_{1,\,i}$ is individual incomes at time t+1, and n_q the number of households in quantile q. $\Delta y_{q,\,i}$ is the change in income of each household in each quintile brought about by growth.

Plutocratic Approach

In this approach, each household receives an amount of income based on its share in the total income within its quantile:

$$y_{1,i}^{pluto} = y_{0,i,q} + \frac{y_{q,i}}{y_q}\Delta \hat{y}_q = y_{0,i,q} + \Delta \tilde{y}_{q,\,i}$$

where $\frac{y_{q,i}}{y_q}$ reflects the share of the household in each quintile out of total income of that quintile.

Sectoral models

The heterogeneity of income growth among households is a crucial factor, especially in least developed countries, where high levels of inequality exist. This is because per capita GDP growth differs across sectors of the economy and, therefore, does not translate into similar income growth rates across the income distribution.[18] To analyze this heterogeneity across sectors[19] further, we use two different models: a three-sectors model (agriculture, industry, and services) and a more flexible eleven-sector model.

To project poverty levels based on the growth of different sectors of the economy, we first identify the household members with the highest income and designate them as the heads of the household. Next, we determine their sector of employment. Figure 1 displays the percentage distribution of employed household heads across three and eleven sectors. The figure provides valuable insights into the distribution of employment across different sectors, which help better understand the relationship between sectoral growth and poverty levels.[20] Computing the sector of household employment based on highest earner and assigning the growth rate of that sector for household income growth could bias the results if there are small difference across multiple earners in the household. These could potentially affect the poverty projections for sectoral model. To account for this, we have also used shares of income of household members working in different sectors as weights to arrive at augmented sectoral growth for that household. The projections broadly remain the same when these growth rates are used.

[18] Income growth differs across sectors/occupations and there is profound inequality in access to opportunities to different sectors and occupations. For instance, small-scale farmers with lack of financial capital and credit constraints will not have high productivity.

[19] We assume that households stay within the same sector for both periods. In case of large number of sectors (e.g., 11 sector model), and for longer periods, this assumption seems more rigid.

[20] For a household where no working household member is reported (and hence no sector can be assigned), we assume the growth rate of household consumption to be equivalent to GDP growth (like in the one sector model).

Table A1: Poverty Impact using international poverty line, 2020-2025

Poverty line 2.15							
	FY19	FY20	FY21	FY22	FY23	FY24	FY25
Preferred specification: equation (1)	4.9	4.9	5.9	4.9	4.2	8.0	8.6
Poverty Growth Elasticity		5.0	4.9	4.8	4.9	4.9	4.9
NDG-PT(1)		6.0	4.5	3.1	4.4	2.8	2.2
NDG-PT(0.86)		5.8	4.5	3.3	4.5	3.0	2.4
Democratic		5.8	4.6	3.7	4.3	4.5	4.4
Plutocratic		5.7	4.6	3.6	4.2	4.4	4.4
3-sectors			6.4	4.8	3.3	5.2	3.5
Poverty line lower middle-income class 3.65							
	FY19	FY20	FY21	FY22	FY23	FY24	FY25
Preferred specification: equation (1)	39.8	39.8	42.9	39.6	35.5	41.8	39.6
Poverty Growth Elasticity		39.9	39.8	39.7	39.8	39.8	39.8
NDG-PT(1)		43.1	38.2	33.0	38.0	31.9	28.7
NDG-PT(0.86)		42.7	38.4	34.0	38.1	32.9	30.1
Democratic		42.4	38.8	35.0	37.5	38.0	38.0
Plutocratic		42.4	38.8	35.2	37.5	38.0	37.9
3-sectors			43.3	38.7	33.5	39.6	33.7
Poverty line upper middle-income class 6.85							
	FY19	FY20	FY21	FY22	FY23	FY24	FY25
Preferred specification: equation (1)	84.5	84.5	85.3	84.1	81.9	83.5	81.9
Poverty Growth Elasticity		84.3	84.6	85.0	84.8	84.7	84.7
NDG-PT(1)		86.0	83.7	81.1	83.5	80.5	78.7
NDG-PT(0.86)		85.8	83.8	81.7	83.7	81.0	79.5
Democratic		85.8	84.0	82.2	83.4	83.6	83.5
Plutocratic		85.7	84.0	82.2	83.4	83.6	83.5
3-sectors		84.5	85.4	83.4	80.9	83.3	80.3

Note: Preferred specification follows equation (1), including information from nominal growth from eleven economic sectors to model labor income, and household-specific inflation as described in methodological section until FY23. Due to the lack of disaggregated inflation projections afterwards past FY23 projections are deflated using headline inflation. All other projections rely on headline inflation and nominal growth rates. Growth and poverty changes between 2015/16 and 2018/19 is used to estimate the elasticity for the Poverty Growth Elasticity and the Growth Incidence Curve for the Quintile growth contribution. Estimate poverty growth elasticity for real GDP per capita and poverty between FY16 and FY19 are, for the 2.15, 3.65, and 6.85 international poverty lines, respectively 0.37, 0.05, and 0.1. Neutral distribution model uses a passthrough of 0.86 to reflect the consumption share on total GDP; results using higher (lower) passthrough rates present marginally more (less) pronounced variations of poverty to growth. Quintile growth contribution projections include a Democratic approach, where households within a quantile receive the same per-capita income amount, and a Plutocratic Approach, where each household receives an amount of income based on its share in the total income within its quantile.

APPENDIX B: Supplementary Figure

Figure B1: Labor Market Dynamics in Pakistan