Thailand Trends and Drivers of Poverty
2017-2019
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Thailand Trends and Drivers of Poverty
2017-2019

Following remarkable achievements in poverty reduction over two decades, dropping from 65.2 percent in 1988 to 6.2 percent in 2019, and extreme poverty was all but eliminated. However, Thailand’s progress slowed considerably from 2015 onwards (Figure 1). During 2016 and 2018, a slowing economy, droughts, and declining farm, business and wage incomes resulted in increases in poverty. Poverty decreased again in 2019, but with the COVID-19 pandemic’s severe and negative impact on the economy, this progress may not be sustainable.

This note examines the trends and drivers of poverty and inequality reduction during the past two years, presents a profile of the poor and middle class, and provides an ex-ante analysis of the poverty and distributional impacts of the COVID-19 pandemic.

The following analysis shows that between 2017 and 2019, poverty and inequality declined, as poorer households enjoyed higher levels of growth than richer households. However, this positive trend was driven by redistribution effects rather than an overall growth effect. While households at the bottom of the distribution saw their consumption increase, mainly due to increasing social assistance incomes, growth at the top end of the distribution was marginal, and in some cases, negative. In particular, the decline in poverty in 2019 was due to an expansion of the state welfare program. Furthermore, in late 2019 and 2020 the Thai government focused much of its COVID-19 response efforts on relief for citizens, especially those in vulnerable groups. The addition of emergency social assistance programs since the onset of the pandemic appears to have mitigated the impact of the crisis on poverty, which simulations indicate would have otherwise increased without said social assistance. However, it remains to be seen if relief efforts will continue to counteract the negative economic effects of COVID-19 and sustain poverty levels at their current rates. While the Thai government has approved additional relief packages in 2021, the ongoing global crisis threatens important sectors of the Thai economy, particularly international tourism.
I. Recent Trends in Poverty and Inequality

*Thailand recorded some progress in poverty reduction and shared prosperity in 2019.*

**Poverty and inequality declined during 2018-19.** Based on the upper middle-income class (UMIC) poverty line of US$5.50/day/person (in 2011 Purchasing Power Parity—PPP), Thailand’s poverty rate increased from 7.6 percent in 2017 to 8.4 percent in 2018 and then declined to 6.2 percent in 2019 (Figure 2). As a result of this trend, the number of people living in poverty increased by about 0.5 million between 2017-18 and then declined by 1.4 million in 2019. While in 2017-18, poverty rates deteriorated in rural areas only, in 2018-19, poverty declined mostly in rural areas but somewhat in urban areas as well. The decline in poverty was coupled with a reduction in inequality—the consumption-based Gini coefficient fell from 36.5 percent in 2018 to 35 percent in 2019, and the income-based Gini coefficient declined from 45.1 percent in 2017 to 43.1 percent in 2019 (Figure 3).

**Figure 2. Poverty Rate and Number of Poor, 2017-19**

**Figure 3. Consumption Gini, 2017-19**


**Thailand achieved some progress towards shared prosperity in 2018-19.** Average per capita consumption increased by a mere 0.4 percent for the total population during 2018-19, however for the bottom 40 percent of the consumption distribution, average consumption increased by 5 percent. This is a significant contrast compared with the previous year, when average consumption essentially shrank among the bottom 40 percent (Figure 4). The largest increases in total and food per capita consumption were observed among the poorest decile—which saw respective increases 7.5 and 10 percent in 2018-2019—while the richest deciles experienced a decline in both their food and total per capita consumption (Figure 5). Most of the food consumption increase was in meat, fish and vegetables sub-groups, which rose by between 30 to 50 percent among the poorest groups. Appendix A provides detailed changes in food and nonfood consumption items in 2018-19.

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1 National official poverty rates follow similar trends, increasing from 7.9 percent in 2017 to 9.9 percent in 2018 and then declining to 6.2 percent in 2019.
Average household income also increased for poorer groups between 2017 and 2019. During this period, overall average household income per capita slightly declined by 0.1 percent per year, but it increased by 3.4 percent for the bottom 40 percent. The highest increase in current per capita income was among the poorest decile, while income declined for the top two deciles. The improvement in poorer households’ income is driven by an increase in income from social assistance; wages, salaries and nonfarm business; in-kind receipts; and remittances (Figure 6). Households in all income groups experienced financial losses (in terms of rent and interests from savings and loans), but the loss was highest among the richest groups.

Note: Labor income includes wages and income from work compensation; public assistance includes income from elderly and disability assistance, welfare cards and other assistance programs; financial includes income from rent and interests from savings and lending; remittances include remittances from migrants and other private transfers; in-kind includes imputed rent for free-occupied house and income in-kind from unpaid food and goods. Total income corresponds to current income.


Income data is available only in odd years.
Signs of pro-poor growth are observed in 2019. Economic growth measured by changes in household consumption and income per capita from the SES survey appears to be much lower than growth in GDP. Real GDP per capita grew at an average annual rate of 3.2 percent over the period of 2017 to 2019, while per capita household consumption and income slightly declined by a respective 0.3 and 0.1 percent per year during the same period. The divergence in the survey-based and National Accounts-based data is not unique to Thailand, but it seems to be larger and more persistent than in other economies. While understanding the reasons of this discrepancy is beyond the scope of this paper, Appendix B provides some details on its importance and potential sources. Focusing on survey-based data, the rate of growth of both consumption and income appears significantly higher for the Thai population at the bottom of the distribution than for those who were better off, suggesting a pro-poor growth pattern in 2019. This is apparent in the income Growth Incidence Curve (GIC) for 2017–19, which shows the percent change in average income for each percentile of the distribution, and in the consumption GIC for 2018–19, which shows the percent change in average consumption for each percentile of the distribution. Both curves are downwardly sloped, indicating higher growth amongst the poorest percentiles in 2019 (Figures 7 and 8). More details can be found in Appendix C.

Poverty declined faster among households in vulnerable situations.

Poverty declined faster in the Northern parts of the country than in the other regions. While the North and Northeast remain poorer than the rest of the country, they recorded the fastest decline in poverty between 2018 and 2019, with the poverty rate falling from about 13 percent to 8.6 percent in the North and from 14.2 percent to 10.3 percent in the Northeast (Figure 9). Inequality declined in all regions but fastest in Bangkok, where the consumption-
Based Gini decreased by 3 points. The income-based Gini also fell by nearly 7 points in Bangkok during 2017-19. The fast decline of inequality in the capital city is puzzling and requires further analysis, in particular as consumption-based Gini tends to change slowly.

**Figure 9. Poverty and Inequality by Region, 2017-19**


Poverty declined faster among large households and those in vulnerable employment. Households whose head is out of the labor force (OLF) or employed in agriculture continue to have the highest poverty incidence. While these households experienced an increase in poverty in 2017-18, they also had the highest decline in poverty in the following year. In 2018-19, the poverty rate declined by about 4 percentage points among households whose head is out of the labor force as well as those who worked in agriculture, compared with a decline by 2 percentage points among those whose head is employed and 1.5 percentage points for those whose head works in industry (Figure 10). The decline in poverty was also higher among households headed by women—from 8 percent in 2018 to 5.5 percent in 2019—than those headed by a man—from 8.6 to 6.5 percent. Households with large family size are much poorer than those who have fewer members, but poverty declined faster among these households between 2018-19.

**Figure 10. Poverty Trends by Household Sociodemographic Characteristics, 2017-19, Percent**

II. Drivers of the Reduction in Poverty and Inequality

The decline in poverty seems to be driven by redistribution rather than growth. The decomposition method proposed by Datt and Ravallion (1992) to determine the growth and redistribution components of the decline of poverty shows that, during 2017-19, the reduction in poverty at the national level was entirely driven by a reduction of inequality in the distribution of consumption (redistribution effect), while the lack of growth in household consumption partly offset the decline in poverty, albeit marginally. This is in sharp contrast with the 2015-17 period, when mean household consumption increased (growth effect) but its effect was largely offset by an increase in inequality, resulting in an increase in overall poverty (Figure 11). From 2017-19, redistribution explained most of poverty reduction, which coincides with the expansion of the state welfare card program and expanded aid to farmers in 2019.

![Figure 11. Decomposition of the Change in Poverty, 2017-19, Percentage Points](image)

A. Thailand  
B. Urban-Rural  
C. Region


**Rural areas experienced the largest declines in poverty.** The decomposition of Ravallion and Huppi (1991), which allows us to further understand the contribution of changes among population subgroups to poverty reduction, shows that the decline in poverty during 2017-19 was mainly due to progress in poverty reduction in rural areas and in the North and Northeast regions. While these decomposition methods can help understand some of the drivers of changes in poverty, their utility in policy making remains limited, as they explain changes in poverty on the basis of changes only in summary statistics that are hard to target with policy instruments. Therefore, they must be complemented by additional detailed analysis to better understand the factors that supported poverty relief in Thailand during 2019.

**Two approaches are used to examine in detail the drivers of poverty and inequality reduction during 2017-2019.** The first uses the Recentered Influence Function (RIF) of the unconditional quantile regression method proposed by Firpo, Fortin, and Lemieux (2009, 2018). The method consists of decomposing changes in household consumption (or income) into (1) improvements in household characteristics or endowments, such as more education of the head of the household, ownership of assets, and access to employment opportunities and social assistance programs; and (2) changes in the rewards or returns that they get for those characteristics like returns to education, assets productivity, and profits to business. The two
components can themselves be decomposed to identify specific attributes that contribute to changes in consumption or income. The decomposition is applied to each quantile of the consumption (income) distribution to understand differences in the patterns of change for different welfare groups. The second approach uses the method of Azevedo et al. (2013) and Inchauste et al. (2014) to estimate the contribution of changes in demographic factors and in income from different sources to changes in poverty and inequality. The two approaches complement each other and allow a relatively robust assessment of the drivers of poverty and inequality changes.

**The unconditional quantile decomposition proceeds in three steps.** The first step is to estimate the unconditional quantiles using the RIF-regression approach. The second step involves estimating a counterfactual distribution of consumption for 2018, which represents the distribution of consumption that would have prevailed if returns to households endowments were the same as in 2019. The third step consists of using the counterfactual distribution to decompose the difference in consumption distribution between 2018 and 2019 into one part that is entirely explained by changes in households’ endowments and one part that is only due to changes in returns to those characteristics — for example, the increase in consumption that is only due to an increase in ownership of assets versus the increase in consumption that is only explained by better returns to or more productive use of those assets. In its simplest form, the approach assumes that the conditional expectation of the quantiles can be modelled as a linear function of the explanatory variables, and thus is estimated using the Ordinary Least Squares (OLS) regression. However, when the linearity does not hold, this affects the regression coefficients and thus the endowments and returns effects (Fortin et al. 2010, Rothe 2015, Firpo et al. 2018). The issue can be addressed by adjusting the consumption distribution by a reweighting factor, which can be estimated using a logit or probit model. More technical details about the methodology and the variables used in the regressions can be found in Appendix D.

**The increase of consumption among the poorer groups was primarily driven by the improvement of the returns to their endowments.** Figure 12 shows the overall change in (real log per capita) consumption during 2018-19 at each (unconditional) percentile and decomposes this overall change into endowments and returns effects using the reweighting approach. Figures 12.A and C show the overall change in consumption (the green line), the pure endowments effect (the blue line), the pure returns effect (the orange line), and the specification and reweighting errors (dot lines). Figures 12.B and D show the detailed contribution of explanatory variables (or group of variables) to the endowments and returns effects. During 2018-19, household consumption grew among the poorest decile at 6.8 percent, compared with 2 percent for the median and a decline for the top two deciles. Improvements of households’ endowments contributed 16 percent to the increase of consumption in the lowest decile, and an increase in their returns contributed 84 percent. The increase in consumption

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5 The method is similar to Oaxaca-Blinder decomposition approach but can be applied to various distributional measures, such as quantiles, Gini, interquantiles, and so forth.

6 The results are based on the reweighted-regression decomposition, where the reweighting factor is estimated using the logit model. The probit model shows similar results.

7 The specification error reflects the importance of departures from the linearity assumption of the RIF-regressions and the fact that, except for the mean, the RIF depends on the distribution of log consumption (and thus on the explanatory variables X through their effect on log consumption). The reweighting allows for assessment of the quality of the reweighting (see Appendix D and Firpo et al. (2018) for more technical details).
was the highest among the poorest percentiles at about 10 percent, to which increase in endowments contributed 40 percent and better returns to their endowments and assets contributed 60 percent. The decline in consumption among the better-off groups was driven by a deterioration of both their endowments and returns.

**Figure 12. Drivers of Consumption Change, 2018-2019**

A. **Aggregate Endowments Effect**

B. **Detailed Endowments Effect**

C. **Aggregate Returns Effect**

D. **Detailed Returns Effect**

| Note: The unconditional quantiles are estimated using the Epanechnikov kernel and bandwidths of 0.07. The reweighting factors are estimated using the logit model. |
| Significance: * At the 10 percent level; ** at the 5 percent level; *** at the 1 percent level based on bootstrap standard deviations using 100 replications. |

Ownership of communication means and social assistance programs are the main drivers of the increase in household consumption and thus poverty reduction. The proportion of households in poorest percentile owning a smartphone increased from 56 percent in 2018 to 62 percent in 2019, and in the lowest decile the increase was from 69 to 76 percent. The number
of smart phones in these households also increased quite significantly. This not only contributed to the overall improvement of the endowments of these households but also to the increase in their returns, as they seem to have made more productive use of these assets (Figures 12.B and C, Figure D.1 in Appendix D). The very poor seem also to have been able to increase the productivity of their transportation means, such as motorcycles. Households in the poorest groups (1st to 10th percentile) benefitted from an increase in social assistance. In particular, the proportion of households benefitting from the Thai government cash transfer program launched in 2017, also referred to as the welfare card program, increased from 52 to 70 percent for the 1st percentile and from 60 to 75 percent for the lowest decile. While this contributed positively to the endowments of these households, it seems that the returns generated by these programs grew even faster, contributing significantly to the observed increase in returns. Social assistance for disabled people and assistance from funds to farmers did not increase, but these funds seem to have helped households in low income (consumption) groups generate higher returns. The time proximity between the two surveys does not allow for capturing any significant changes in education, employment or access to basic services. However, households in the poorer groups seem to have experienced a slight improvement in the returns to post-primary and lower secondary education, as well as a small increase in the returns to wage and self-employment. These households also seem to have experienced a slight improvement in access to safe sanitation and access to electricity, which appears to have helped heighten their productivity. The household size declined slightly among the poorer groups, but this did not help reduce the burden they carry from large families and a high number of dependents. The richest groups experienced a quite significant decline in the returns to their employment. Most of the decline occurred among those in high occupations and those who work in the services sector, who also experienced a fall in their assets ownership, mainly phones, computers and cars. Part of these changes is difficult to explain and requires further investigation.8

The decline in poverty and inequality was mostly driven by the improvements in returns from social assistance, smart phones and education. Poverty declined 2.2 percentage points between 2018 and 2019; increases in households’ endowments contributed 23 percent to this decline, and higher returns to their endowments contributed 77 percent (Figure 13.A). The endowments component was entirely driven by the increase in ownership of smartphones and access to welfare card program, and to a lesser extent, access to basic services (Figure 13.B). Better returns from social assistance programs (including the welfare card program) and from post primary and secondary education, more productive use of smart phones, and to a lesser extent higher returns from wage and self-employment were the main contributors to heightened returns and poverty reduction. The consumption-based Gini coefficient declined 1.5 percentage points; improvements in endowments and returns contributed, respectively, 20 and 80 percent to this decline (Figure 13.C). Ownership of smartphones and access to the welfare program contributed to the equalization of the distribution of consumption on the endowments side. Increased returns to wage and self-employment, education and social assistance, as well as more profitable use of smartphones among poorer groups, had the most significant inequality reduction effects (Figure 13.D). The positive effect of access to electricity and improved

8 The decline of assets may be due to their replacement by more modern means that are not included in the survey. Some of the changes related to the decline of welfare among the richest groups and the reduction in inequality, including the impressive reduction in Bangkok, may be driven by adjustments of sample design or weighting, and they require further investigation.
sanitation on people’s productivity also positively impacted poverty and inequality reduction. However, returns from other assets such as transportation and IT tools seem to have a negative effect on inequality reduction. These results point to the importance of expanding education, access to productive jobs, assets and social protection for vulnerable groups. In 2019, about 70 percent of household heads in the poorest decile did not go beyond primary education, and only 10 percent completed lower secondary or above. While expanding education will result in a decline of returns, particularly for low education levels, it remains the best shield against poverty and the primary way to open up opportunities. Only 27 percent of household heads in poorer groups work in salaried jobs and over 60 percent are concentrated in self-employment, where productivity and profitability remain significantly lower than in wage employment. This points to the fragility of the gains made and the importance of undertaking actions to firm up these achievements to prevent their reversal.

Figure 13. Drivers of Poverty and Inequality Reduction, 2018-2019, Percentage Points


Note: Change in inequality is measured using the Gini coefficient.

The poverty decomposition method complements the unconditional quantile decomposition to allow a better understanding of the drivers of poverty reduction. The unconditional quantile regression allows us to understand how changes in the distributions of observed household characteristics between two periods contribute to welfare (consumption or income), how the returns to these characteristics vary across the entire distribution and how
they contribute to poverty and inequality changes. However, the method does not allow for the estimation of the contribution of changes in income from labor or other sources to poverty and inequality changes. The poverty decomposition method helps address this limitation but does not allow us to assess the contribution of changes in endowments and returns to changes in poverty and inequality statistics. Moreover, the approach takes advantage of the additivity property of a welfare aggregate to construct a counterfactual unconditional distribution of the welfare aggregate by changing each component individually to calculate its contribution to the observed changes in poverty and inequality; as such, it does not allow for identification of the causal mechanism driving the changes. For example, it does not capture the effects of labor income increases on eligibility for safety nets programs and thus changes in incomes from cash transfers or social assistance programs. More technical details can be found in Appendix D.

Public assistance income was the major contributor to the increases in market income and reduction in poverty over the period 2017–19. Figure 14 shows the sources of changes in poverty during 2017–19. The y-axis shows the percentage point contribution to the change in the poverty rate. When the contribution is positive, that component contributed to an increase in poverty, and the opposite for a negative contribution. The components of household income per capita are described in Annex D. The results indicate that the government continues to rely on public assistance to boost incomes of lower-income households. While market income had been declining until 2019, the persistent support of government policies to supplement households’ incomes seems to have borne fruit. Income from public assistance was the most important driver of poverty reduction at the national and regional levels, particularly in the North and Northeast, where the poverty decline was the highest. At the national level, the percentage of households receiving public assistance income increased from 53 percent in 2017 to 65 percent in 2019. The government cash transfer program (welfare card program), from which 35 percent of households benefitted, contributed to boosting incomes in Thailand. However, there were criticisms that the program was not well targeted and resulted in leaks to a large number of nonpoor. While the program covered 73 percent of the poor in 2019, it also benefitted 33 percent of nonpoor, making the proportion of the nonpoor in all beneficiary households significantly higher than the poor (91.5 vs 8.5 percent). About 9 percent of the population in the 9th decile and 4 percent of those in the 10th decile benefit from the program. Financial income and income in-kind, followed by remittances, also had a significant contribution to poverty reduction. The results of the decomposition of inequality support the results in Figure 13, indicating that income from public assistance, and to a lesser extent, from wage employment and business, contributed to inequality reduction.

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9 As income is not available in 2018, the decomposition can be applied only to the period 2017-19.
Figure 14. Sources of Changes in Income-based Poverty, 2017-2019, Percentage Points


Decline in farm income partly offset the positive trends and was the largest contributor to the increase in poverty. Net business and net farm incomes are one of the highest sources of income in urban and rural areas, respectively. From 2017 to 2019, farm income declined for the whole population and the poorest groups, while business income increased slightly among the poorest groups but declined overall. Farm income and to a lesser extent, business income, had a negative effect on poverty decline. Wage growth was positive in Bangkok and the central region but negative in the rest of the country, thereby having a small impact on poverty overall.

The decline in the share of the population that is employed also affected income negatively and reduced the pace of poverty reduction. The share of employed people declined from 73.4 percent in 2017 to 72.2 percent in 2019. Most of the decline occurred in the North (from 70 to 67 percent), the Northeast (74 to 72 percent) and the South (78 to 76 percent). In contrast, employment increased in Bangkok and the Central region. These changes partly offset the positive effects of public assistance and remittances on poverty reduction.

Overall, the decline in poverty does not seem to be driven by dynamic changes in the economy. While the decline in poverty reflects positive changes in Thailand, the drivers of these changes do not augur well for the sustainability of these achievements. Most of the improvements in living conditions seem to be driven by public assistance, while there were no changes in labor income, employment or productivity, suggesting risks for the continuation of these improvements and for the creation of a prosperous society.

10 The negative contribution of business income to poverty reduction despite an increase, on average, of net business income among the poorest group is due the decline in the proportion of households (among the poorest group) who are deriving income from business and a reduction in the share of business income in total current income.
III. Profile of the Poor versus the Middle Class

The proportion of the population classified as poor and vulnerable slightly declined since 2017, while the middle class has marginally increased. For easy comparison with countries in the region, we classify the population into five economic classes. These include extreme poor as per capita household consumption below $1.90 a day, 2011 PPP; moderate poor as between $1.90 and $3.20; economically vulnerable as between $3.20 and $5.50; economically secure as between $5.50 and $15; and global middle class as above $15. The first three categories encompass Thailand’s poor. In 2019, the global middle class represented 37.5 percent of the population (22.3 million), and this proportion remained stable over the past three years—declining from 37.4 percent to 36.9 percent in 2018 and then increasing to 37.5 percent in 2019. The economically secure class represented 56.3 percent (33.5 million) in 2019, up from 55 percent in 2017, suggesting that those who escaped poverty moved to this class. Thailand’s economically secure and global middle classes are significantly larger than developing East Asia and Pacific (EAP) averages—estimated at respectively 47 and 17 percent.11 Bangkok, followed by the Central region, have the largest shares of global middle class, while in the northern part of the country, the majority of the population is in the economically secure class (Figure 15).

Nearly 40 percent of Thailand’s households are headed by women, and they belong to better-off groups. In both 2018 and 2019, women-headed households made up around 39 percent of Thai households – 38 percent of rural households and 40 percent of urban ones. People living in female-headed households are more likely to be better off than those in male-headed ones; about 5.5 percent of those in female-headed households are poor and 38 percent belong to the middle class, compared to, respectively, 6.5 percent and 37 percent of those in male-headed households (Figures 16.A and 16.B). The majority of male household heads are married, while a large proportion of female household heads are widowed or single (Figure 16).

11 This is based on averages from available surveys over 2015-17 in developing EAP countries, which include Cambodia, China, Fiji, Indonesia, Lao People’s Democratic Republic, Malaysia, Mongolia, Myanmar, Papua New Guinea, Philippines, Solomon Islands, Thailand, Timor-Leste, and Vietnam.
16.C). Households whose head is single are those with proportionally more members in the middle class (69 percent of their members are middle class), while those whose head is widowed have proportionally more economically secure members (63 percent of their members are economically secure and 30 percent are middle class). Overall, poverty rates are slightly lower among households headed by married women (5.7 percent) than those headed by married men (6.9 percent) and among households whose head is a divorced man (3 percent) than those headed by divorced women (5.3 percent). While male and female heads tend to have similar age profiles, male heads have higher education levels; 62 percent of male heads did not go beyond primary education compared to 68 percent of female heads (Figure 16.D). Female-headed households have, on average, slightly smaller family sizes but a higher number of dependents, mainly elderly, than male-headed ones (dependency ratios are 0.5 for male-headed households and 0.6 for female headed ones). Female headed households have also more female members (1.6) than male-headed ones (1.3) and fewer employed members (1.4 vs 1.7).

**Figure 16. Economic Class and Gender of Household Head**

A. Distribution of Economic Classes for Male-Headed Households, 2019, Percent  
B. Distribution of Economic Classes for Female-Headed Households, 2019, Percent  
C. Marital Status by Gender of the Head, Percent  
D. Education Level by Gender of the Head, Percent


**Poor households have larger families and more dependents than the middle class.** The average family size of poor households is about 1.6 times higher than the middle class, and the average number of children is over three times higher. About 33 percent of households with four or more children under 15 are poor, over five times higher than the national average and 24 percentage points more than the poverty rate for households with just one or two children. Poor households have also more elderly members, who represent around 17 percent of their

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family, compared with 13 percent for the middle class. Furthermore, poor households have more disabled members, who represent about 6 percent of their family members, compared with 2 percent for the middle class. Poor households are also less likely to be headed by a woman than economically secure and middle-class households (Figure 17).

Figure 17. Demographic Profile of the Poor and Middle Class, 2019

<table>
<thead>
<tr>
<th>Average number of children under 15</th>
<th>Poor</th>
<th>Secure</th>
<th>Middle class</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.5</td>
<td>0.9</td>
<td>0.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Average family size</th>
<th>Poor</th>
<th>Secure</th>
<th>Middle class</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.9</td>
<td>3.8</td>
<td>3.0</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Female-headed Households</th>
<th>Poor</th>
<th>Secure</th>
<th>Middle class</th>
</tr>
</thead>
<tbody>
<tr>
<td>35%</td>
<td>38%</td>
<td>40%</td>
<td></td>
</tr>
</tbody>
</table>

Note: the poor correspond to those living below $5.5/day/person- 2011 PPP.

The poor live predominantly in rural and northern areas, although there are some differences in residential patterns by the gender of household head. Over 80 percent of the poor live in rural areas and 70 percent are located in the northern part of the country, compared with respectively 37 and 26 percent of the middle class (Figure 18.A). The economically secure tend to live more in rural areas (67 percent) than urban areas, and about half of them are located in the northern regions. Among poor households, around 83 percent of male-headed ones live in rural areas compared to 78 percent of female-headed households (Figure 18.A); this is a slight change from 2018, when 80 percent of poor male-headed households and 79 percent of poor female-headed households were rural. The proportions of rural households within economically secure and middle class groups are comparable for both male- and female-headed households, although there appears to be a consistent trend of a smaller proportion of female-headed households in rural locations than male-headed households for each economic class (Figure 18.A). Poverty rates declined for both male- and female-headed households from 2018 to 2019, but the decline was slightly higher for female headed ones (2.5 vs 2.1 percentage points). This is due to the larger decline of poverty among rural female-headed households (3.7 percentage points) than rural male-headed households (2.7 percentage points). While poverty rates remain comparable for households with heads of both genders in urban areas, the reverse gender gap widened in rural areas from 0.5 percentage points in 2018 to 1.5 percentage points in 2019 (Figure 18.B).
The poor are disadvantaged by too little education. Access to basic services does not seem to be problematic for the poor, however it is worth mentioning that the poor rely mostly on bottled water (55 percent) and rain water (18 percent) for drinking, while 66 percent of middle class households drink bottled water and 29 percent drink treated tap water (Figure 19). Thailand seems to lack a piped system to deliver safe drinking water. Similarly, only 17 percent of poor households have access to a flush toilet compared with 73 percent in the middle class. Educational attainment is very low among the poor; about 13 percent of poor household heads have no education, and 77 percent did not complete further than primary school. This is in sharp contrast with middle class, for whom about half of household heads have upper secondary or university degrees. Among the economically secure, only 22 percent of household heads went beyond primary education. Education remains the best shield against poverty, though primary and lower secondary education no longer seem sufficient to open up opportunities. The poverty rate exceeds 17 percent among households whose heads have no education and drops to 1 percent or less among those whose heads attained upper secondary or university education. However, the education gap between the poor and other groups is smaller among younger populations, but prominent in higher levels of education. Only 6 percent of poor individuals aged 18 to 25 have no education while 23 percent have completed upper secondary school. Among the middle class in the same age group, 1 percent have no education and 30

percent have completed upper primary school. However, only 2 percent of poor individuals 18 to 25 years old have university education and above compared to 41 percent of members of the middle class in the same age group, suggesting a constraint to future opportunities.

Figure 19. Living Conditions of the Poor and Middle Class, 2019

<table>
<thead>
<tr>
<th>Access to Basic Services</th>
<th>Safe Drinking Water</th>
<th>Improved Sanitation</th>
<th>Electricity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poor</td>
<td>95%</td>
<td>99%</td>
<td>99%</td>
</tr>
<tr>
<td>Middle class</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Education level household head</th>
<th>None</th>
<th>Primary or less</th>
<th>Lower second.</th>
<th>Upper second.</th>
<th>University</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poor</td>
<td>14%</td>
<td>77%</td>
<td>5%</td>
<td>3%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Middle class</td>
<td>2%</td>
<td>32%</td>
<td>13%</td>
<td>24%</td>
<td>23%</td>
</tr>
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Note: Education levels of household’s heads of economically secure groups are very close to middle class ones.

The poor are concentrated in low productivity employment and rely heavily on public assistance and remittances. About 35 percent of poor household heads are out of the labor force, 11 percentage points more than the middle class (Figure 20). Those in the labor market are predominantly self-employed (64 percent) and in the agricultural sector (72 percent). Middle class household heads work mostly in commerce and services, with only 15 percent in agriculture. They are also mostly in wage and salaried employment, which offers more stability and security. Less than 2 percent of the heads of poor households are in high or medium skilled occupations (such as managers, professionals or clerical support workers) compared with 29 percent for the middle class. Poor households rely heavily on vulnerable income sources from farming, business and in-kind payments, with labor income representing only about 28 percent of their average income. Public assistance and remittances represent, respectively, around 13 and 10 percent of poor households’ income. Without public assistance, the poverty rate would have been over 4 percentage points greater in 2019. Similarly, without remittances the poverty rate would have been more than double the current rate. In contrast, the middle class rely mostly on income from labor (48 percent of their average income) and to a lesser extent, income from business (20 percent). Income from remittances and from public assistance represent a small proportion of these households’ income, accounting for 7 percent and 2 percent, respectively, of their total incomes. Although a smaller proportion of middle-class households receives remittances (20 percent compared to 43 percent), the average value received is three times higher for these households than for poor households. The average net income from business for the middle class is over 9 times larger than for poor ones, suggesting that the latter tend to run very small businesses and therefore earn smaller profits.
Poor female household heads are more likely to be out of the labor force and are more concentrated in unpaid family work and services than their male counterparts. Among poor female household heads, 48 percent are out of the labor force, as compared with 29 percent of poor male household heads – a difference of 19 percentage points (Figure 21.A). This pattern is apparent among economically secure and middle-class household heads as well, and the labor force gender gap is largest for economically secure household heads (22 percentage points). Despite an overall reduction in poverty, the proportion of household heads out of the labor force increased overall for both men and women from 2018 to 2019, from 15 percent to 20 percent for men and from 35 percent to 40 percent for women. Poor female household heads were 10 percentage points more likely to engage in unpaid family work than poor male household heads in 2019, a pattern that persisted in wealthier economic classes (Figure 21.B). This suggests that female-headed households are less economically stable than male-headed households. Furthermore, in all economic classes, female household heads were more likely than male household heads to be employed in the service sector, with a difference of 6 percentage points for poor households and 14 percentage points for economically secure and middle class households (Figure 21.C).
Female-headed households are more reliant on remittances as a source of income. Despite female-headed households making up 39 percent of all households in 2019, 48 percent of households that received remittances in 2019 were headed by women. Overall, 41 percent of female-headed households received remittances in 2019 compared to 28 percent of male-headed ones; 47 vs 34 percent in rural areas and 34 vs 21 percent in urban zones. Remittances represent a larger share of the female-headed households’ income than male-headed ones (12 vs 6 percent), and the gender gap is larger in rural areas than urban ones (Figure 22). A greater proportion of female-headed households than male-headed households received remittances in each economic class; 50 vs 42 percent in the poor group, 48 vs 37 percent in the economically secure group and 32 vs 16 percent in the middle class. Female-headed households in poor and middle-income classes are more reliant on remittances as a source of income than their male counterparts, with remittances making up over a 4-percentage point larger share of their income (Figure 23). The average monthly per capita value in remittances received by poor female-headed households is close to 30 percent higher than the average value received by poor male-headed households, while the average monthly per capita value in remittances received by middle class female-headed households is more than 2.5 times the average amount received by middle class male-headed households. Without remittances, the poverty rate for female-headed households...
households would have been nearly 11 percentage points higher than the actual 2019 rate, while the poverty rate for male-headed households would have been almost 8 percentage points higher. Female-headed households’ demonstrably greater reliance on remittances may be attributable to migrant husbands or older sons.

Figure 22. Income Sources by Gender of the Head and Location, 2019, Percent, 2019

Figure 23. Income Sources by Gender of the Head and Economic Class, 2019, Percent


Poor households own significantly less assets than the middle class. While ownership of communication means such as smart phones, motorcycles and TV is high among the poor, they still lack more valuable assets such cars and computers (Figure 24). Middle class households own all durable consumer goods such as washing machines, fridges, and computers at higher rates than poor households. There is an especially large gap for air conditioners, which are owned by 59 percent middle class households compared to only 2 percent of poor households, the largest difference in any asset ownership. Female-headed households are less likely to own transportation assets than male-headed households in all economic classes (Figure 25). Among the poor, female-headed households are 7 percentage points less likely to own a motorcycle and 14 percentage points less likely to own a private car in comparison to male-headed households; these gaps decrease to 5 and 12 percentage points respectively for economically secure households and 3 and 8 percentage points respectively for middle class households.

Figure 24. Living Conditions of the Poor and Middle Class, 2019.

IV. Potential Impact of COVID-19 on Poverty

The Thai government’s response to COVID-19 has been rapid and multifaceted, including public health measures, social protection, and fiscal policy. Although Thailand was the second country to report cases of COVID-19, the rapid public health response resulted in fewer than 3,800 cases and only 59 deaths as of September 2020. Early on, the government instituted a lockdown, followed public health experts’ recommendations, and implemented effective contact tracing, all of which were met by high levels of societal cooperation. However, successive waves of COVID-19 have proven challenging for the country, with the number of cases surging above 2,000 per day in May of 2021 (Thailand Economic Monitor (TEM) 2021). Early on, the government’s spending increased to meet economic challenges with cash transfers – mainly to vulnerable populations – and a SME lending program, which was further expanded in 2021 (TEM 2020, 2021). While the initial relief and stimulus spending will be fully disbursed by September 2021, the government approved an additional support package of 500 billion Baht in May 2021 (TEM 2021). Fiscal policy measures have focused on bank liquidity, low inflation, and debt restructuring, allowing the financial system to remain stable (Jitsuchon 2020, TEM 2021). However, high levels of household debt, corporate weaknesses, tightening SME loan requirements by commercial banks and a growing fiscal deficit (from 2.3 percent of GDP in 2019 to 5.9 percent in 2020, to a projected 9.6 percent in 2021) remain concerns (TEM 2020, TEM 2021).

COVID-19 has resulted in a severe economic contraction and decreased revenues from international tourism. Thailand’s economy is predicted to be most negatively impacted in the ASEAN region (Thomas 2020). GDP contracted 12.1 percent in the second quarter of 2020 and an overall 6.1 percent in the full year, representing one of the most dramatic declines in the region (TEM 2020, TEM 2021). From Q1 to Q2 of 2020, Thailand’s current account surplus fell from 6.6 percent to 0.6 percent of GDP – although it reached 1.9 percent of GDP by Q1 of 2021 – largely because of border closures in April 2020 and the resulting decrease in international tourism. Tourism businesses are struggling; only 49 percent of tourism MSMEs believe that they can make it through the COVID-19 crisis and 23 percent of these businesses are on the verge of closing or have closed for good (Thomas 2020). Domestic tourism remains
below normal levels and will be insufficient to fill the revenue gap left by the drop in international tourism.

**Projections for economic recovery depend heavily on international tourism.** GDP growth is projected to reach to 2.2 percent in 2021 and increase to 5.1 percent in 2022, when output would return to pre-pandemic levels of 2019 (TEM 2021). However, international demand for goods and services will recover slower than domestic demand. While private investment and manufacturing had recovered somewhat by Q1 of 2021, the services and agricultural sector remain hampered, both by the pandemic and by drought. Furthermore, given the ongoing nature of the COVID-19 crisis – including new global variants of the virus, a second and third wave in Thailand, and faltering worldwide vaccination rollouts – the prospects of increasing international tourism in 2021 appear slim. As such, quick recovery of the international tourism industry – a key sector for Thailand – seems uncertain. The GDP growth forecast for 2021 has been revised downward to 2.2 percent (from an initial estimated 3.4 percent) and economic activity is not expected to return to its pre-pandemic levels until 2022, with the recovery being projected to be slow and uneven.

**COVID-19 struck an economy already suffering from several structural weaknesses, including the prevalence of low-quality jobs and informal employment.** Surveys of Thai workforce and micro and small businesses conducted by the Asia Foundation in May and September 2020 show that during the onset of the pandemic — from March to May — about 70 percent of the national workforce saw their income fall by nearly half, with informal sector workers and low-income households being hit the hardest. Over 500,000 jobs were lost in manufacturing, wholesale & retail trade and accommodation & food services, and there was a progressive return of workers back to agriculture. Until September 2020, recovery was very slow, with only 8 percent of workers reporting improvements and over a quarter of tourism businesses remaining closed. An additional survey conducted by the Asia Foundation in June 2020 showed that informal and low-income workers are continuing to suffer. While 70 percent of the national workforce saw monthly incomes fall by an average of 47 percent, informal sector workers saw an average decline of 67 percent; furthermore, higher proportions of workers in the lowest income groups have seen declines in income than those in other income groups, and 49 percent of small business owners stated that their businesses were at risk of closing (TEM 2021). The 2019 SES data shows that around 30 percent of the working age population is out of the labor market and about 63 percent of those employed are in informal jobs. Sectors most affected by disruptions during the COVID-19 crisis, such as commerce and construction, are also those with shares of informal workers exceeding 70 percent. The existing labor market challenges and the new ones created by the pandemic are complicated by a rapidly aging population.

**Children and youth were severely affected during the early onset of the pandemic.** A UNICEF survey from April-May 2020 found that about 77 percent of families with young children experienced declines in incomes, job reductions, or increases in expenditures, as

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12 Informal employment is based on the occupation category (e.g., elementary occupations, craft workers), employment class (e.g., self-employed, unpaid family workers) and non-contribution to social security. ILO (2020) shows that, in 2019, the share of employment in the informal economy was 54.3 percent, totaling about 20 million workers without contributory social protection or paid and sick leave.
compared with 68 percent of families without young children. The survey also revealed that only 38 percent of children were prepared for remote learning, with the most common reasons for unpreparedness being a lack of a device, parents’ time, parents’ IT skills, and internet. UNICEF survey data indicate that the pandemic has been particularly challenging for children with disabilities, for whom social distancing and access to health services can be more difficult.

Results from our simulation model show that without a firm and massive response from the Thai government, poverty would have increased by around 1.2 percentage points in 2020, adding about 780 thousand poor people and 270 thousand poor children. As the crisis continues to unfold, uncertainty remains high about the potential socioeconomic effects of the pandemic. To overcome some of the data limitations, we use a macro-microsimulation model to assess the poverty and distributional impacts of the pandemic over the next three years. The model combines population and macroeconomic projections with pre-crisis data from the 2019 SES to predict income and consumption at the individual and household levels. The model uses labor markets as the main transmission mechanism and allows for two types of shocks: (1) shocks to labor income, including employment shocks and earnings shocks from the pandemic, and (2) shocks to non-labor income, including changes in private transfers and changes in social protection mechanisms (in this case, the emergency transfers in response to COVID-19 – see Box 1). More details about the model are in Annex E. Figure 26.A shows that with a contraction of GDP per capita by 6.1 percent in 2020 and without emergency assistance from the government, poverty would have increased to 7.4 percent in 2020. With the resumption of GDP per capita growth at 3 percent in 2021 and 4.8 percent in 2022, the poverty rate would have reached 7 percent and 5.9 percent in 2021 and 2022, respectively. This would have represented about an additional 780,000 people entering poverty in 2020, of which around 270,000 are aged 0 to 14 years (Figure 26.B). Inequality would have increased as well, with the consumption-based Gini coefficient increasing from 35 percent in 2019 to over 36 percent throughout 2020-22 and the income-based Gini coefficient rising from 43 to 44 percent during the same period. Simulation results suggest that successful implementation of the COVID-19 response assistance program, and assuming perfect targeting, would have helped maintain poverty rates 1.2 percentage points lower and inequality around 0.5 to 1 percentage point lower during 2020 and 2021 compared to the scenario where no additional transfers were given; in the simulation model with transfers, the consumption-based Gini coefficient is estimated at 35.5 percent and the income-based Gini at 43 percent during 2020-22.

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13SES data for 2020 became available very recently. While the survey includes the needed information to assess changes in poverty and living conditions, it does not include information on the sources of income, which are collected in odd years only. The ongoing High Frequency Survey will help to overcome part of the data limitations.

14 The relatively small impact of the crisis on poverty and inequality is due to the low proportion of labor income (the income source most affected by the pandemic) as a share of total household income – 28 percent for the poor and 39 percent for the total population – as well as low employment-growth elasticity. Estimates from the PovSim simulation model (Lakner, Negre and Prydz 2014) indicate higher rates of poverty for Thailand in 2020 than estimated here, but the approach is less robust because it does not capture labor market behavior and distributional changes generated by the crisis.
Figure 26. Impact of COVID-19 on Poverty

A. Poverty Rate Projection, Percent

B. Number of Poor Projection, Millions

Source: Projections based on SES 2019, using macro-microsimulation model.
Note: Projections for 2022 assume that emergency response programs will end.

Box 1: Emergency Social Transfers in Thailand during COVID-19

The Thai government quickly responded to the arrival of COVID-19 in the country, passing a 1-trillion Baht Borrowing Decree in April 2020 to address health needs, relief, and economic recovery; a majority of this package (555 billion Baht) was set aside for relief, including cash transfers and subsidies. Eligible groups for cash payments were self-employed workers, farmers, low-income workers, people insured under section 33 of the social security fund, people holding Social Welfare cards, infants, seniors, and people with disabilities. By the end of Fiscal Year 2020, 81 percent of the original amount social assistance funds had been disbursed. The Thai government allocated an additional 331 billion Baht towards social assistance from October 2020 to March 2021 as the second wave of COVID-19 hit the country, about two thirds of which were designated for supporting households through the same programs as the original relief package. Most recently, the government announced a third package in May 2021 of 225 billion Baht; this package mainly targets the private sector. Funds for social assistance in the newest package will once again primarily extend relief programs from the initial intervention, although a new scheme (“Ying Chai Ying Dai”) was introduced, which refunds 10-15 percent of purchases of food, products, and services via e-vouchers. This program will mainly benefit middle and high-income classes and is intended to spur domestic consumption. Furthermore, the Thai government announced in the same month that it will increase borrowing by 500 billion Baht, 300 billion of which (1.9 percent of GDP) will be allocated to cash transfers. An estimated more than 44 million Thais have benefitted from social assistance and social insurance programs during the pandemic; some estimates suggest that over 80 percent of households benefitted from social assistance during 2020.

Source: Thailand Economic Monitor 2021

Transfers are likely to have been particularly impactful in vulnerable regions. Based on the simulation results, and compared to 2019, the presence of social assistance transfers would have decreased poverty rates in rural areas by 0.2 percentage points in 2020 and 1.2 percentage points in 2021 (instead of increasing by, respectively, 1.5 and 0.8 percentage points without the transfers), while poverty in urban areas would have increased by 0.5 percentage points in 2020 and 0.2 percentage points in 2021 with the transfers (rather than an increase of 1 and 0.8
percentage points, respectively, without the transfers). Results further indicate that the government’s response measures effectively reversed impacts on poverty in the poorest regions of the North and Northeast, where poverty is estimated to have declined a respective 1 and 0.3 percentage points in 2020 instead of increasing by over 1.1 percentage points in both regions (Figure 27).

Figure 27. Impact of COVID-19 on Poverty, by Region

A. Projections without Transfers

B. Projections with Transfers

Source: Projections based on SES 2019, using the Microsimulation Model.

Simulations show that those entering poverty in 2020-22 are predominantly rural, less educated, unemployed or working in less productive sectors. Nearly 70 percent of those entering poverty in 2020 as well as those entering poverty through 2021-22 are expected to come from rural areas (Figure 28), reflecting the continuing vulnerability of rural households to income shocks.  

Regionally, of those falling into poverty, over 25 percent are based in

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15 This is due to the prevalence of poverty in rural areas compared to urban zones and to the persistence of structural challenges that limit government efforts in reducing poverty and vulnerability.
Central Thailand, while around 35 percent or more are from the Northeast. Particularly notable are the education levels of those falling into poverty; of those newly entering poverty, approximately half have less than primary education, while under 20 percent have at least upper secondary education. Only around half of the new poor are employed, while the rest are either unemployed (around 20 percent) or out of the labor force (about 30 percent). Those employed are predominantly working in agriculture or in traditional services.

**Figure 28. Profile of those Falling in Poverty, 2020-2021, Percent**


Notes: New poor are those who were not poor in 2019 but became poor in, respectively, 2020, 2021 and 2022. Traditional services include commerce, transport and accommodation & food services, and household activities. Modern services include public administration, financial services, ICT and education. The grouping of sectors is based on their exposure to the impacts of the pandemic on economic activities. More specifically, accommodation & food services and transport are known to be among the most severely affected sectors, while public administration, ICT and financial services were less exposed.

**Preliminary figures from the Socio-Economic Survey (SES) for 2020 support the modeled findings.** Estimates based on SES 2020 yield quite similar figures to the simulation model with social transfers for 2020, with estimates showing poverty slightly increasing by 0.2 percentage points in 2020, representing an additional 200,000 people falling into poverty (Figure 29.A). Similarly, the 2020 SES estimates consumption-based Gini at 35 percent. The 2020 SES also finds that poverty rates increased in urban areas by 0.5 percentage points and remained unchanged at 8.9 percent in rural areas. However, there are few discrepancies between 2020 SES data and the microsimulation model results at the regional level: while both show a slight reduction of poverty in the North and a small increase in the South, the SES 2020 shows a decline of poverty in the Central region by 0.8 percentage points and an increase in the Northeast by 1.6 percentage points, while the microsimulation model finds an increase in poverty by 1.1 percentage points in the Central region and a decline by 1 percentage point in the Northeast. While both SES 2020 and the simulation model with social transfers show that poverty rates did not change between 2019-2020 for male-headed households as well as urban female-headed households, the SES 2020 shows an increase of poverty for rural female-headed households, while the simulation model with transfers shows a decline by 0.2 percentage points.
for this group (Figure 29.B). The comparison of simulation results with and without transfers shows that the emergency program helped urban male-headed households slightly more than urban female-headed ones, and rural female-headed households slightly more than rural male-headed ones.

The observed discrepancies between the finding from the SES 2020 and the microsimulation model with social transfers are due to the assumption of perfect targeting of social transfers in the simulation model, as well as changes in population weights in the SES 2019 and 2020 surveys. In the simulation model, social transfers are allocated to individuals and households based on the eligibility criteria (and amounts) of each program. As there is no available information to identify who truly received the transfers, the model assumes that all eligible individuals benefitted from the programs. The validation of the simulation model results is performed by comparing results from different simulation scenarios where recipients of the transfers are selected at random. Findings from the different test models are comparable to those discussed here. In the simulation model, household and population weights for 2020 (and subsequent years) are estimated using weights from SES 2019 and UN population projections for Thailand by gender and age groups. The comparison of SES 2019 and 2020 weights shows a much larger increase in the population size than the projected increase in UN population estimates (4.1 percent vs 0.7 percent), with relatively important variations at the regional level. While the targeting assumptions about social transfers and changes in the weights seem to have led to discrepancies between the SES 2020 and microsimulation model findings, the differences remain minimal (and mostly within the confidence interval), which supports the robustness of the results.

Figure 29. Poverty by Area and Gender, 2020
A. Poverty Rates and Number of Poor, SES 2020.

Source: SES 2020 and simulation model.

16 SES 2020 questionnaire did not include questions that allow us to identify who benefitted from the COVID-19 emergency response programs. This limitation can be partly addressed once the HFS data is available.

17 SES 2019 weights underestimate the total population size (59.5 million in the survey compared to around 69 million in UN population data). It seems that adjustments were introduced in 2020 SES to produce a more realistic estimation of the population size (at around 62 million), which explains the observed population growth between the two surveys.
The impact of the pandemic led to some changes in sectors of employment. According to the SES 2020, there were no major changes in employment and unemployment rates during 2019-20 among both the poor and the total population, although this contrasts slightly with Bank of Thailand data, which shows an increase of total unemployment from 1 to 1.7 percent. The simulation results also show a slight increase in total unemployment to 2.5 percent and a more substantial increase of unemployment among the poor. The pandemic also seems to have induced some transitions from manufacturing, and to a lesser extent from other industries, to agriculture. The changes during the pandemic appear to have occurred primarily among the poor; while the poor remain concentrated in agriculture, the proportion of poor in this sector increased by 2.2 percentage points during 2019-20, while the proportion of poor in manufacturing and other industries declined by 1.8 and 0.4 percentage points, respectively (Figure 30).

**Figure 30. Employment Status, 2019 & 2020, Percent**

Source: SES 2019 and 2020.
References


https://openknowledge.worldbank.org/handle/10986/17681


Figure A.1. Changes in Food and Tobacco Consumption by Decile, 2018-2019, by Category, Percent

Figure A.2. Changes in Non-food Consumption by Decile, 2018-2019, by Category, Percent

Annex B. Divergence in Growth Trends Between National Account and Survey Data

Table B.1. Per Capita Incomes and Expenditures in the Thailand

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<tr>
<td>GDP per capita</td>
<td>167,464</td>
<td>178,752</td>
<td>182,725</td>
<td>183,731</td>
<td>188,728</td>
<td>194,473</td>
<td>201,684</td>
<td>209,393</td>
<td>213,854</td>
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<tr>
<td>Private final consumption expenditure per capita</td>
<td>85,321</td>
<td>91,148</td>
<td>91,601</td>
<td>91,694</td>
<td>93,702</td>
<td>96,044</td>
<td>98,667</td>
<td>102,846</td>
<td>106,625</td>
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<tbody>
<tr>
<td>Expenditure per capita</td>
<td>63,220</td>
<td>68,153</td>
<td>69,236</td>
<td>69,116</td>
<td>72,344</td>
<td>72,079</td>
<td>73,284</td>
<td>72,567</td>
<td>72,580</td>
</tr>
</tbody>
</table>

| National Accounts | GDP per capita Growth (%) | 0.4 | 6.7 | 2.2 | 0.6 | 2.7 | 3.0 | 3.7 | 3.8 | 2.1 |
|                  | Private final consumption expenditure per capita Growth (%) | 1.8 | 7.3 | 1.0 | 0.5 | 2.6 | 2.9 | 3.1 | 4.6 | 4.0 |

| Household SES | Expenditure per capita Growth (%) | 1.9 | 7.8 | 1.6 | -0.2 | 4.7 | -0.4 | 1.7 | -1.0 | 0.0 |

Sources: Household survey figures are based on Household Socio-Economic Survey; National Accounts figures are calculated based on National Income of Thailand (NI) published by the Office of the National Economic and Social Development Council (NESDC); values are in 2011 THB.

National accounts show consistent increases in GDP and consumption, while household expenditures from the Thai household survey show small changes in recent years. A difference in the levels and growth rates of GDP and private consumption has existed for a number of years, as seen in Table B.1. There are a number of possible reasons for these discrepancies. Household survey data does not account for consumption by foreigners, while the National Accounts do; because international tourism generates high revenues in Thailand, this may be an important factor. Furthermore, household surveys tend to underestimate private consumption because the wealthiest households are under-represented in survey samples, and those that appear in the samples may be less likely to disclose their full incomes. On the other hand, National Accounts may overestimate GDP growth because shifts to market-bought goods and services from home-produced ones as households transition to higher income groups are not reflected in the data, just as home production is not captured in National Accounts.
Annex C. Savings and Growth Incidence Curve Consumption.

Figure C.1. Saving in 2017 by Decile, Percent

Figure C.2. Saving in 2019 by Decile, Percent


Note: As income is negative for some households due to negative profits in farm and nonfarm business, adjusted savings treat negative incomes as zero.

The pattern of savings in 2019 contrasts with the savings pattern in 2017 across almost every decile group. The saving rates in the lowest two deciles increased by about 3 percentage points, while savings in the middle quintile increased from sharply below zero to 23 percent and 13 percent in adjusted savings (Figures C.1 and C.2). In the top decile, savings decreased by more than 10 percentage points for both savings and adjusted savings. The change in the top decile is further suggestive of redistributive policies leading to reduced savings.

Figure C.3 Growth Incidence Curve Consumption, 2017-2018, Percent

Annex D. Drivers of Poverty Change

Unconditional quantile decomposition.

The Recentered Influence Function (RIF) regression approach (Firpo, Fortin and Lemieux 2009 and 2018) provides a simple regression-based procedure for performing a detailed decomposition of different distributional statistics such as quantiles, variance and Gini coefficient. The RIF-regression model is called unconditional quantile regression when applied to the quantiles (percentiles, deciles etc.). The technique consists of decomposing the change in consumption between 2018 and 2019 at various quantiles of the unconditional distribution into changes in endowment such as education, ownership of assets, access to basic services etc., also called the *endowments effect*, and changes in the returns to these characteristics, called the *returns effect*. These components are then further decomposed to identify the specific factors that contribute to the changes in consumption.

The procedure is carried out in three steps. The first step consists of estimating the unconditional quantile regressions on log per capita consumption for 2018 and 2019. The second step serves to estimate a counterfactual consumption distribution for 2018 – that is, the consumption level that would have been realized in 2018 if returns to endowments were the same as in 2019. The third step involves the comparison of the counterfactual and empirical distributions to estimate the part of the consumption change that is only attributable to changes in characteristics or endowments and the part only explained by changes in returns to those characteristics. The *endowment* and *return* components can be further divided into the contribution of each specific characteristic variable.

The method can be easily implemented as a standard linear regression, and an ordinary least squares (OLS) regression of the following form can be estimated:

\[
RIF(y, Q_\theta) = X\beta + \epsilon
\]

where \( y \) is log per capita consumption, and \( RIF(y, Q_\theta) \) is the RIF of the \( \theta \)th quantile of \( y \) estimated by computing the sample quantile \( Q_\theta \) and estimating the density of \( y \) at that point by kernel methods:

\[
RIF(y, Q_\theta) = Q_\theta + \frac{\theta - I\{y \leq Q_\theta\}}{f_y(Q_\theta)},
\]

\( f_y \) is the marginal density function of \( y \) and \( I \) is an indicator function. \( X \) is the regressors matrix including the intercept, \( \beta \) is the regression coefficient vector and \( \epsilon \) is the error term. The regressors include nine groups of variables: (1) Demographic characteristics: age, gender and marital status of the household head and size of the household; (2) Education (six education categories): no education, incomplete primary, complete primary and less than lower secondary, lower secondary, upper secondary, university and above; (3) Employment sectors: agriculture, industry, trade, public administration, and other services; (5) Occupations: high, medium, elementary, and skilled agriculture; (6) Access to basic services: water, sanitation and electricity; (7) Assets ownership: dummies for various assets; (8) Social assistance: dummies for welfare card, fund for farmers, pension, school lunch, scholarship, disability assistance, and for other social assistance; (9) Geographic location fixed effects.
Model (1) is estimated for the 10th to 90th quantiles and uses the below decomposition in which traditional Oaxaca-Blinder (OB) decompositions are applied to the consumption distribution by percentile:

\[
Q_\theta^{i^*} - Q_\theta^i = \{Q_\theta^{i^*} - Q_\theta^i\} + \{Q_\theta^i - Q_\theta^i\} = (\bar{X}^i - \bar{X}^i)\hat{\beta}_\theta^M + \bar{X}^i (\hat{\beta}_\theta^M - \hat{\beta}_\theta^F)
\]  

\[
\hat{Q}_\theta^{i^*} - \hat{Q}_\theta^i = \Delta^\bar{X} + \Delta^\bar{S}
\]

where \(Q_\theta^{i^*}\) and \(Q_\theta^i\) are the \(\theta\)th unconditional quantiles of log per capita consumption for 2019 and 2018 respectively, \(\bar{X}^i\) the vectors of sample averages of household characteristics, and \(\hat{\beta}_\theta^M\) the estimates of the unconditional quantile partial effect. \(\hat{Q}_\theta^i = \bar{X}^i \hat{\beta}_\theta^{i^*}\) is the counterfactual quantile representing the distribution of consumption that would have prevailed in 2018 if households received the same returns for their characteristics as in 2019.

The first term on the right-hand side of equation (2) represents the contribution of the differences in characteristics to the change in consumption at the \(\theta\)th unconditional quantile, or endowment effect. The second term of the right-hand side of the equation represents the change in consumption due to changes in returns to those characteristics at the \(\theta\)th unconditional quantile.

The endowment and return effects can be further decomposed into the contribution of individual specific characteristics (or group of some characteristics) as follows:

\[
\hat{Q}_\theta^{i^*} - \hat{Q}_\theta^i = \sum_k (\bar{X}^i_k - \bar{X}^i_k) \hat{\beta}_{\theta,k}^{i^*} \text{ and } \hat{Q}_\theta^i - \hat{Q}_\theta^i = \sum_k \bar{X}^i_k (\hat{\beta}_{\theta,k}^{i^*} - \hat{\beta}_{\theta,k}^i)
\]

(3)

where \(k\) designates the individual specific household characteristics.

Equation (1) is based on the standard linearity assumption between the dependent variable and the covariates \(X\) used in the OB decomposition. When the linearity assumption does not hold, the model can lead to estimation errors (Fortin et al. 2010 and Firpo et al. 2018). The problem can be addressed by using a reweighted regression approach and the reweighted-regression decomposition of the overall change in consumption can be specified as follows:

\[
Q_\theta^{i^*} - Q_\theta^i = (\bar{X}^i \hat{\beta}_\theta^{i^*} - \bar{X}^i \hat{\beta}_C^{i^*}) + (\bar{X}^i \hat{\beta}_C^{i^*} - \bar{X}^i \hat{\beta}_\theta^i)
\]

\[
\hat{Q}_\theta^{i^*} - \hat{Q}_\theta^i = \Delta^\bar{X} + \Delta^\Delta^\bar{X}
\]

(4.a)

Where \(\hat{\beta}_C^{i^*} = (\sum_{i=1}^{M} \Psi (X_i) X_i X_i')^{-1} (\sum_{i=1}^{M} \Psi (X_i) Q_{Mi} X_i)\) and \(X_C = \sum_{i=1}^{M} \Psi (X_i) X_i\)

The composition effect in equation (4.a) can be divided into a pure composition or endowment effect (first term in equation 4.b) and a component linking to the specification error in the linear model (second term in equation 4.b):

\[
\Delta^\bar{X} = \Delta^\bar{X} + \Delta^\Delta^\bar{X}
\]

(4.b)

Similarly, the structural effect in equation (4.a) can be divided into a pure structural or returns effect (first term in equation 4.c) and a reweighting error component (second term in equation 4.c):
If the model was truly linear, the specification error term would be equal to zero, as both the weighted and unweighted regressions would yield the same consistent estimates, where \( \text{plim} \left( \hat{\beta}_{\theta}^{i^*} \right) = \text{plim} \left( \hat{\beta}_{\theta}^{i} \right) = \beta_{\theta}^{i} \). Computing the specification error is thus important for checking whether the linear model is well specified, and for adjusting the composition effect in the case where the linear specification is inaccurate. When the reweighting factor is consistently estimated \( \text{plim} \left( \bar{X}_C^i - \bar{X}^i \right) = 0 \)

The reweighting factor \( \Psi(X) \) is a simple function of \( X \) that can be easily estimated using standard methods such as a logit or probit. Consider the dichotomous variable \( D_M \) indicating the year: \( D_M = 1 \) for 2019 and \( D_M = 0 \) for 2018.

The reweighting factor can be expressed as:

\[
\Psi(X) = \frac{P(D_M = 1|X) \times P(D_M = 0)}{P(D_M = 0|X) \times P(D_M = 1)}
\]

The conditional probabilities \( P(D_M = 1|X) \) and \( P(D_M = 0|X) \) can be estimated using a logit or probit specification and then used to estimate \( \Psi(\bar{X}) \).

The decomposition of the consumption change in the reweighted model (as expressed in equation 4) proceeds in the following steps: Estimate the reweighted factor \( \Psi(\bar{X}) \), compute the counterfactual quantiles using the reweighted consumption, and decompose change in consumption into pure composition and structure effects as well as specification and reweighting errors at each selected quantile of the consumption distribution.
Figures D.1 shows the endowment and returns effects as well as the specification and reweighting error of selected variables or group of variables for the first ten percentiles.

Figure D.1 Endowment and Returns Effects of Selected Factors by Poorest Percentiles

**Poverty decomposition.**

Poverty is a function of household consumption, and changes in poverty can be decomposed into the factors as illustrated in Figure D.2. The decomposition is an identity and can be expanded or reduced based on data availability. For example, labor and non-labor income can be further decomposed if desired.

**Figure D.2. Household Consumption per capita – a Decomposed Identity**

Income data are reported in monthly units and include cash and in-kind sources. Labor income is the total of wages, salaries, and income from work compensation or terminated payment. Non-labor income includes all other sources of income. No adjustments are made to these components, with the exception of aggregating some common elements to reduce the number of components to be used in the Shapley decomposition. The number of paths of the Shapley-Shorrocks increases exponentially when adding more components. To reduce the number of components, financial and in-kind sources of income have been aggregated.
<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor</td>
<td>1) Wages and Salaries</td>
</tr>
<tr>
<td></td>
<td>5) Income from work compensations or terminated payment</td>
</tr>
<tr>
<td>Net Business</td>
<td>2) Net profit from business</td>
</tr>
<tr>
<td>Net Farm</td>
<td>3) Net profit from farming</td>
</tr>
<tr>
<td>Pension</td>
<td>4) Income from pensions/annuities, other assistances</td>
</tr>
<tr>
<td>Remittances</td>
<td>6) Income from money assistance from other people outside the household</td>
</tr>
<tr>
<td>Public Assistance</td>
<td>7) Income from elderly &amp; disability assistance, and other government programs</td>
</tr>
<tr>
<td>Financial</td>
<td>8) Income from rent of house / land and other properties (including license and copyright)</td>
</tr>
<tr>
<td></td>
<td>9) Income from saving interests, shares, bonds, and stocks</td>
</tr>
<tr>
<td></td>
<td>10) Income from interests of individual lending</td>
</tr>
<tr>
<td>In-Kind</td>
<td>11) From rental estimated of free-occupied house (including own house)</td>
</tr>
<tr>
<td></td>
<td>12) From unpaid of goods and services</td>
</tr>
<tr>
<td></td>
<td>13) From unpaid of food and beverages</td>
</tr>
</tbody>
</table>
Annex E. The Macro-microsimulation Model

1. Approach

The model combines macroeconomic projections with pre-crisis micro data from household and/or labor force surveys to predict income and consumption at the individual and household levels, which can then be compared to measure poverty and distributional impacts. Figure 1 presents a stylized representation of the methodology.

The model focuses on labor markets as the main transmission mechanism and allows for two types of shocks: shocks to labor income, modeled as employment shocks, earnings shocks or a combination of both; and shocks to non-labor income, modeled as a change to social protection mechanisms and private transfers. Shocks can be positive or negative depending on the trends outlined by the macroeconomic projections. Minimum assumptions are made about other sources, such as capital and financial income or public transfers, as discussed below.

The data requirements can be summarized as follows. At the macro level, information is needed on projected (i) output, employment, and labor earnings growth; (ii) population growth by gender and age groups and (iii) predicted price changes. At the micro level, information is needed on (i) labor and non-labor income and consumption, and (ii) labor force status and basic job characteristics, including earnings. Needless to say, the reliability and accuracy of the simulation results is a direct function of the quality and level of detail of the information available at the macro and micro levels.

Finally, the income and consumption projections from the model can be used to produce a variety of outputs, including aggregate poverty and inequality comparisons across scenarios, poverty and vulnerability profiling of specific groups and/or areas, and various summary measures of distributional impacts, such as growth incidence curves and state transition matrices.

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18 The model uses projections for growth of overall GDP per capita and GDP per capita by sector (agriculture, manufacturing, other industry, traditional services and modern services) over 2020-22.
1.1 Overview of simulation exercise

A brief overview of the mechanics underpinning the simulation exercise is presented in Figure 2. The exercise can be broken down into three distinct steps: calibration, simulation and assessment of impacts.

**Calibration.** Calibration is the process by which household and individual-level information is used to model labor market behavior and outcomes. This is done in three steps. First, we model labor force status for all working age individuals (above 15 years old) as a function of household and individual characteristics, where labor force status can be non-employed, employed in agriculture, manufacture, other industry, traditional services or modern services. Although ideally, we would like to work with a more detailed menu of options (e.g. “employed in tradeable” and “employed in non-tradeable” instead of “employed in industry”), the number of labor force states that can be considered is dictated by the level of disaggregation available for the macro projections. We then use a multinomial logit to estimate the parameters of the model, as well as the individual-level probability of remaining in a particular state and/or changing to a different one, as given by (1). The approach is similar to that used in Ferreira et al (2008). We estimate the model separately for high and low-skill individuals to allow for structural differences in the labor market behavior of the two groups.

\[
I_{i,j=s} = \text{Ind}[a_s + z_i b_s + u_i^s > a_j + z_i b_j + u_i^j \mid \forall j \neq s]
\]  

---

19 We estimate a reduced form of the household income-generation model which is based on Bourguignon and Ferreira (2005) and Alatas and Bourguignon (2005)
20 This includes “out of the labor force” and “unemployed.” The decision to pool both states into a single category is motivated by the fact that the unemployment rate is extremely low in Thailand, even during crisis times.
21 For Thailand, low and high-skilled refer to individuals with education levels below and above completed upper secondary, respectively.
where \( s = \text{Labor force status}; \ G = \text{labor skill level (high/low)}; \ z = \text{gender, age, education, region, remittances, and land ownership}. \)

Second, we model labor earnings for all employed individuals ages 15 years old or more as a function of individual and job characteristics and use a standard Mincerian OLS regression to estimate the parameters of the model, as given by (2) (similar to Ferreira et al. 2008). We use a fairly broad definition of labor earnings for the purpose of the exercise that includes wages and salaries, but also income from self-employment. This is particularly important in the case of agriculture and for economies with large informal sectors, such as Thailand, since wage and salaried workers constitute a limited fraction of those employed in these sectors. It may lead, however, to a loss in precision and/or predictive power given that the structural relationship between individual and job characteristics and earnings could be different for salaried and non-salaried workers. To allow for maximum flexibility and (indirectly) account for some of these differences, we estimate the model separately for each of the five sectors, i.e. agriculture, manufacture, other industry, traditional services and modern services and for low and high-skill workers.\(^{22}\)

\[
\log w^G_i = \alpha^G_s + x_i \beta^G_s + v^G_{s,i}
\]

(2)

where \( x = \text{gender, age, education, region, and indicators for salaried and public employment}. \)

Finally, we model non-labor income with a focus on social protection transfers and make some minimal assumptions about other sources of non-labor income.

**Simulation.** Simulation is the process by which information on aggregate projected changes in output, employment and remittances is used to generate changes in labor and non-labor income at the micro level using the structural models developed as part of the calibration.\(^{23}\) This is done in four steps.\(^{24}\) First, we use population growth projections to adjust for demographic changes between 2019 (base year) and 2020-2022. In practical terms, taking into account population growth allows us to explicitly take into changes in the size of the working age population, and hence to distinguish between employment growth driven (or rather absorbed) by demographic trends and net (or additional) employment growth.

Secondly, we use the projections from the labor force status and labor earnings models to replicate projected changes in aggregate total and sectoral output and employment. We start with employment and calculate the total number of individuals that need to be reassigned between employment and non-employment and across employment sectors in order to match projected aggregate changes in total and sectoral employment. We then use the estimated

\(^{22}\) Notice that, although we could estimate separate models for salaried and non-salaried workers based on the information from the household survey, we would not be able to use these models for the purpose of predicting future earnings since we do not have earnings and employment information disaggregated by salaried/non-salaried workers from macro data.

\(^{23}\) We do not assure consistency (i.e that absolute aggregate magnitudes are equal) between the data set used at the two modeling stages (see Bourguignon et. al 2008). Additionally, we assume equal changes at macro and micro levels. We cannot run a test if macro changes are similar or not to micro changes because of lack of a panel data at micro level (see Deaton 2001 and Bourguignon et al 2008).

\(^{24}\) This sequence for introducing changes in the model is based on Vos et al (2002)
probabilities from the multinomial model to select candidates for reassignment. The direction and magnitude of flows between employment and non-employment and across sectors of employment is given by changes in the relative shares of different status with respect to the reference population. For instance, whether individuals must be reassigned from non-employment to employment or vice-versa depends on whether the employment rate of individuals ages 15 and older is increasing or decreasing. Similarly, workers are expelled from sectors whose relative share in total employment is declining and absorbed into sectors whose relative share in total employment is increasing will absorb workers (note that this is independent of whether employment in a sector is growing or contracting in absolute terms).

The sequence in which individuals are reassigned across states and sectors matters for the final simulation results, so we briefly describe here the procedure we follow:

- **Step 1** - Flows between employment and non-employment: If the employment rate is increasing, non-employed individuals with the lowest predicted probability of being non-employed will be reassigned. If the employment rate is declining, employed individuals with the highest probability of being non-employed will be reassigned. Reassignments will continue up to the point where the change in the employment rate at the micro level matches the change at the macro level.

- **Step 2** - Flows out of contracting sectors: For sectors whose share of total employment is declining, those individuals with the lowest predicted probability of being employed in the sector will be selected out and added to the pool of “eligible” workers to be employed in growing sectors (notice this pool also contains those who have been reassigned from non-employment if the total employment rate is growing). Reassignments out of each sector will continue up to the point where the change in the sector employment share at the micro level matches the change at the macro level.

- **Step 3** – Flows into growing sectors: Individuals in the pool of “eligible” workers will be assigned to growing sectors on the basis of their predicted probability of being employed in each sector. Assignments are made sequentially with the sector whose employment share is growing fastest absorbing workers first and the sector whose employment share is growing the slowest absorbing workers last. Reassignments to each sector will continue up to the point where the change in the sector employment share at the micro level matches the change at the macro level.

There are a few important features of this process that are worth mentioning. The reassignments described in steps 1 to 3 are calibrated so as to replicate net aggregate flows between employment and non-employment and across sectors. In reality, movements across these different states are quite significant, so that gross flows are usually larger than net flows. The order of proposed steps is such that it allows for non-employed individuals to become employed and employed individuals to become non-employed, but also for individuals to

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25 We add error terms which represent the unobserved heterogeneity of agents’ labor supply behavior. These lead to some disparateness in responses to a change in the labor demand, capturing the fact that in the real-world, individuals who are identical in observables might still respond differently to the same change in labor demand.
change sectors. In doing this we try to capture the fact that highly “employable” individuals are more likely to remain employed in one sector or another, at times at the expense of less “employable” workers (i.e., highly “employable” workers will crowd others out when employment opportunities become relatively scarcer).

We next use the earnings model estimated as part of the calibration to predict earnings for two groups of workers: those with no previous earning history (i.e. non-employed in 2019) and those who change sector of employment. Because earnings are a function of both observable and unobservable individual and job characteristics, we add a random element to the predicted earnings produced by the model to account for unobserved heterogeneity. For all other individuals, we use the earnings information available in the household survey.

Once all workers have been assigned positive labor earnings, total earnings in a sector are adjusted to match aggregate projected changes in output. This step relies on the fact that that projected changes in sectoral output can be explained by projected changes in sectoral employment and projected changes in sectoral earnings and profits, and assumes that earnings and profits grow at the same rate.

The treatment of public sector workers and those with more than one job differs slightly from what we just described. Total public sector employment is assumed to remain constant (i.e. no individuals are assigned to or out of the public sector) and labor earnings of public sector workers are adjusted in line with their sectoral mapping (agriculture, industry or services). Similarly, for those holding more than one job, we assume the sector of employment of their secondary activity remains constant while earnings are adjusted in line with sectoral changes.

The third step in the simulation process pertains to changes in social protection payments. We assign social transfers based on the eligibility criteria (and amounts for each program). We run several simulations with random allocations to test the robustness of the results.

Finally, we simulate changes in other sources of non-labor income. For this we assume that capital and financial income grow at the same rate as real GDP, and domestic remittances change at the rate estimated by the Bank of Thailand.

**Assessment of Impacts.** Impact assessment is the process by which we use the information on individual employment status and labor income, as well as on non-labor income at the household level, to generate income and consumption distributions and construct various poverty and distributional measures that can then be used to compare the crisis and the benchmark scenarios. This is done in three steps.

First, we use CPI changes to account for inflation.

Second, we calculate total household income by aggregating labor income across all employed individuals and adding non-labor income, and then use information on household size to construct a measure of per-capita household income, as in (3).

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26 Specifically, we draw an individual error from the error distribution generated during the estimation.
\[ PCI_m^* = \frac{\left( \sum_{i=1}^{k_m} W_i^* I_i^* + y_m^{NL} \right)}{k_m} \]

Third, because poverty Thailand is measured on the basis of per-capita consumption, we need to map income to consumption. We do this by assuming that the household-level consumption-to-income ratio remains unchanged between 2019 and 2020. This is a strong assumption, but the best we can do given the available information. We run random forest regressions to estimate the marginal propensity to consume, but results failed to replicate the baseline scenario.

\[ PCE_{m}^* = PCI_m^* \times \frac{PCE_{2005}}{PCI_{2005}} \]

Finally, we use information on household and individual income and consumption levels to evaluate the poverty and distributional impacts of the crisis by comparing poverty and other outcomes between the benchmark (without crisis) and “with crisis” scenarios.

1.2 Limitations and caveats of the simulation exercise

The proposed approach has some appealing features, the primary one being its capacity to generate income and consumption counterfactuals at the individual and household levels that can then be used to assess impacts across the entire distribution. However, it also has some important limitations that must be taken into account when interpreting the results presented below. We discuss these below.

Firstly, the quality and accuracy of the simulation output is a function of the nature and quality of data underpinning the exercise. More specifically, the results would depend not only on the micro-models, but also on the macro projections of the crisis and the benchmark or no-crisis scenarios. In a typical ex-ante assessment of this type, building the counterfactual to evaluate impact is especially tricky because the comparison between the situations “with” and “without” the “treatment” (the macro shock) is purely virtual or notional. This is particularly important with regard to the output and employment projections since they are key drivers of the results in the absence of a CGE or similar model. In addition:

- The ability to account for heterogeneity across sectors, groups, and others depends on the level of disaggregation of the available macro projection. For instance, the behavior of the tradeable and non-tradeable sectors within industry can only be modeled separately if output growth projections are available for each sector.

- The ability to accurately predict employment and earning changes depends on the available information and on the assumptions needed to correct for information gaps. For instance, in the absence of projections on total and sectoral earnings growth, we need to assume that earnings and profits grow at same rate within a sector. How realistic this assumption is would depend on the country and sectoral context.
The ability to model remittances depends on the quantity and quality of the available data on migrants and remittances, particularly for countries with rapid and/or volatile growth of remittances.

Secondly, the simulations implicitly assume that the structural relationships estimated as part of the calibration process on the baseline data continue to be valid in the future years for which the projections are made. The more distant in the past the baseline year is, the more questionable this assumption is likely to be. In the case of the Philippines, for example, the baseline year is 2018, which is a full four years away from the prediction in the final year (2021). This particular caveat, however, links directly back to the constraints imposed by availability of data. In most countries, household survey data that is available for analysis and processed to the extent necessary for the analysis is likely to predate the prediction years by at least 3 to 4 years.

The third caveat relates to our decision to work with income, rather than consumption data. The advantage of using income is that it allows us to link welfare impact on households directly with potential channels of impact, which are employment, labor earnings and remittances. There are two primary caveats to working with income data: (i) income data often tends to be of lower quality than consumption data, which introduces an element of noise into the analysis due to the unobserved presence of measurement error; (ii) certain assumptions, which can be challenged on the grounds of realism, are needed to convert predicted income levels into consumption and consumption-based welfare measures. It is important to note, however, that caveat (ii) would not be necessary for countries that use an income-based measure of poverty, which is the case in most Latin American countries.

The approach we have adopted to convert income into consumption assumes that the ratio of consumption to income is unchanged for every household between the baseline and prediction years. The constant savings rate that this assumption implies is probably more realistic for poor households than for better-off households. This also implies that our approach may overestimate the consumption impact of the crisis on better-off households, since such households may compensate for an income loss by reducing savings (or dis-saving), resulting in a smaller impact on consumption.

Fourthly, our model does not explicitly account for labor demand at the sectoral level and instead assumes that the labor market conditions mirror (or are proxied by) the macroeconomic projections. The simple approach we adopt implicitly assumes stable relationships between output, demand for labor and labor earnings, which may not hold due to the distortions (such as segmentation and downward stickiness of nominal wages) that typically exist in the labor market and are likely to affect adjustments during a crisis.

Related to the above point, the simplifying assumptions for the labor market also do not account for the possibility of structural shifts in labor demand due to the crisis. Sectoral movements of labor are modeled as depending only on individual/household characteristics (through the multinomial logit model) and population growth. This cannot take into account the kind of structural shifts that have apparently been observed in some countries, such as a reduction in the relative demand for skilled labor. That said, structural changes (for example, in relative
demand for skills) can be incorporated into our model if there exists prior analytical work that provides parametric estimates of how these changes may have affected labor earnings.

The final limitation, related to validation of hypothesis, applies to all ex-ante approaches including ours. The only validation or test for our simulation model is to combine ex-ante and ex-post analysis (see Bourguignon and Ferreira, 2003). Since ex-post data will not be available for some time, some uncertainty about the validity of the simulations generated by this ex-ante method is bound to remain.