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Understanding poverty dynamics in Ethiopia: Implications for the likely impact of COVID-19

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Abstract

We aim at identifying vulnerable groups that face a higher risk of falling into poverty due to the COVID-19 pandemic. Applying a synthetic panel data approach, our analysis of poverty and vulnerability transitions during the pre-COVID period shows not only a high rate of poverty persistence in Ethiopia but also a high probability of moving from vulnerable nonpoor status to poor status. Given the observed persistence of poverty and greater risk of downward mobility, even in the pre-COVID period, it is highly likely that poverty persistence and downward mobility will be aggravated during the current pandemic. A detailed poverty profiling exercise shows that households where the household head is less educated, engaged in the service sector, self-employed, and a domestic worker are population segments with a high rate of downward mobility. As the emerging evidence on the socioeconomic impact of COVID shows, these segments of the population are also the ones relatively more affected by the pandemic. Overall, the pandemic is likely to result in a serious setback to the progress made in poverty reduction in Ethiopia. Poverty reduction policies should thus target not only the existing poor but also the vulnerable nonpoor.

KEYWORDS

Ethiopia, mobility, poverty dynamics, synthetic panel, vulnerability

JEL CLASSIFICATION
I31; I32; D31; O55

1 | INTRODUCTION

Ethiopia has witnessed rapid economic growth since the mid-2000s. For instance, over the sample period considered in this study (2011–2016), the country registered an annual gross domestic product (GDP) growth rate above 9% (World Bank, 2020a). Poverty reduction through sustained economic growth has been one of the overarching development objectives in Ethiopia, particularly since the start of the new millennium. Therefore, the government of Ethiopia has implemented various national development plans and strategies with a particular focus on poverty reduction. During the period 2010/2011–2015/2016, the strong economic growth performance matches visible progress in poverty reduction. In particular, between 2010/2011 and 2015/2016, the proportion of people living below the national poverty line decreased by 21%, from 29.6% to 23.5% (World Bank, 2020a). Compared to the share of people living below the national poverty line in 2000 (44.2%), this amounts to a 20.5 percentage point decrease and can be considered major progress (World Bank, 2015).

However, there is visible spatial heterogeneity in terms of the extent of poverty reduction. For instance, between 2010/2011 and 2015/2016, while urban poverty decreased by 42%, rural poverty decreased by 16%. See also Stifel and Woldehanna (2014) for a detailed discussion of poverty trends during 2000–2011 and the heterogeneities in the observed trends. In particular, these authors document steady but uneven progress during the period in question—while urban areas experienced the greatest gains in the first half of the decade, rural areas realized their gains in the latter half of the decade.

In the current changing world, maintaining such gains in poverty reduction appears to be a major challenge as adverse unanticipated shocks increase the risk of vulnerability and therefore impede the progress made in poverty reduction. This is particularly the case in the context of Ethiopia as shocks related to food and fuel prices, heavy reliance on rain-fed agriculture, recurrent droughts, internal conflicts, and the recent desert locust invasion are likely to increase the vulnerability of households, particularly those living in rural areas. In addition, the current COVID- 19 pandemic, apart from its immediate impact on the health of Ethiopian citizens, is likely to push vulnerable households into poverty as the various containment measures are likely to decelerate economic activity by slowing down the production and distribution of goods and services, among others. It is thus important to identify both the poor and the vulnerable nonpoor and to profile their socioeconomic characteristics. This can help us not only to understand the factors responsible for poverty transitions and lack thereof but also to assess which sections of the society are likely to be highly affected by the impact of the COVID-19 pandemic.

In view of the above, this study aims at taking a fresh look at poverty dynamics in Ethiopia during the COVID-19 pandemic. Analysis of poverty dynamics requires observing the poverty status of units at different points in time, and this requires the use of panel data. However, as a large and nationally and subnationally representative panel data set is lacking in Ethiopia, we employ the synthetic panel data approach, following Dang and Lanjouw (2013) and Dang et al. (2014), using the last two rounds of the Household Consumption Expenditure (HCE) survey (2010/2011 and 2015/2016) data.

The HCE is a large repeated cross-sectional survey that is representative at both the national and subnational levels.[1] Thus, the recent methodological advances in applications of synthetic panels make it possible to move the focus of poverty analysis away from the study of poverty trends and toward the study of poverty dynamics (Hulme & Shepherd, 2003).

The use of a synthetic panel based on a large repeated cross-sectional survey is one major contribution of this study. This is particularly the case as large and representative real panel data sets are not always available, due to the relatively high cost of collecting such data sets. Even when actual panel data sets are available, using synthetic panel data sets might have added value, as analysis based on panel data sets is vulnerable to biased estimates due to the risk of sample attrition and issues related to measurement errors. Synthetic panel data overcome these problems associated with actual panel data sets and are well suited to analyzing poverty dynamics. This is in contrast to cross-sectional data sets, which can provide the estimates of poverty rates at only one particular point in time.

The rest of the study is structured as follows. Section 2 presents the data and methods. Section 3 presents the results and related discussion. Section 4 reviews the emerging evidence on the socio-economic impact of COVID-19 and provides an assessment of the likely impact of COVID-19 on poverty and vulnerability in Ethiopia. Finally, Section 5 provides the concluding remarks.

2 | DATA AND METHOD

2.1 | Data

The HCE survey data were collected by the Ethiopian Central Statistical Authority to provide household-level consumption expenditure data. Thus far, five rounds of HCE surveys have been conducted: 1995/1996, 1999/2000, 2004/2005, 2010/2011, and 2015/2016. In each survey round, new households are sampled, making the data a repeated cross-section. In constructing the synthetic panel, we make use of the last two rounds of the survey.[2] These surveys are conducted at a similar time, making concerns of seasonality less of an issue. This attribute makes the HCE survey suitable for analyzing the dynamics of poverty in Ethiopia using a synthetic panel approach. Using the HCE survey to analyze poverty dynamics in Ethiopia is also appealing as this survey is used by the government of Ethiopia to generate official data on income measures of poverty.

The sample size of the HCE survey has been increasing over the years, reaching 27,830 and 30,255 households in 2010/2011 and 2015/2016, respectively. The sampling design, together with the large sample size, makes the HCE survey data representative at both the national and subnational levels.

Moreover, the HCE survey data contain all the relevant modules that one needs to replicate the official poverty rate, as well as to predict household consumption. These variables include household demographics and household head characteristics, occupations of household members, area of residence, and detailed data on expenditures.

The outcome of interest, consumption, is measured in the same method across the different waves. We use the consumption aggregate from the HCE survey to generate the real household consumption expenditure per-adult equivalent used in this paper. In particular, real per-adult equivalent consumption expenditure is generated by first dividing aggregate consumption expenditure by an adult equivalent scale to consider the differences in the calorie intake/requirement of different age and gender groups within the household. We have then deflated consumption per-adult equivalent by spatial and temporal price indices to arrive at real consumption per-adult equivalent. To calculate the poverty headcount measure, the real per-adult equivalent consumption expenditure is compared with the national poverty lines for the two survey years. The poverty lines used for 2010/2011 and 2015/2016 are 3,781 and 7,184, respectively. By doing this, we manage to replicate the official poverty estimate reported by the government.

The national and regional headcount poverty rates for 2011 and 2016 computed using the HCE data are presented in Tables A3 and A4. In the latter table, the estimates are performed by restricting the age of the household head.

2.2 | Method

As pointed out earlier, having a longitudinal data set is desirable when analyzing poverty dynamics. However, such a data set is usually lacking for a representative sample of households, especially in developing countries. To overcome this problem, researchers develop a statistical method of creating synthetic (pseudo-panel) data sets using repeated cross-sectional data sets (Dang et al., 2014). The idea of analyzing dynamic phenomena using pseudo-panel data constructed from repeated cross-sectional data sets was first developed by Deaton (1985). Over the years, other researchers have extended this method and applied it in the analysis of poverty dynamics (see, e.g., Bourguignon et al., 2004; Bourguignon & Moreno, 2018; Dang et al., 2014; Dang & Lanjouw, 2013; Garcés-Urzainqui et al., 2021; Himanshu & Lanjouw, 2020).

The use of a synthetic panel based on multiple rounds of cross-section data allows one to use time-invariant characteristics to predict household per-capita consumption for the year where the actual observation is missing. The time-invariant characteristics are mainly related to characteristics of the household head, including variables like ethnicity, language, sex, education, place of birth, and parental education. These characteristics are observed in both survey rounds, but for different households, as our data are based on repeated cross sections.

Using the predicted per-capita consumption and for a given poverty line, bound and point estimates of different measures of poverty dynamics can be estimated. One can generate measures of chronic and transient poverty by calculating, respectively, the shares of households in different poverty status categories considering all survey rounds together (joint probabilities) and shares of households in different poverty status categories given their status in the other period (conditional probabilities) (Dang & Lanjouw, 2013). For technical details regarding the synthetic panel data method and the assumptions needed to generate the bound and point estimates of poverty dynamics, the reader is referred to the methodological paper by Garce´s-Urzainqui et al. (2021).

Apart from identifying households in a given population as poor versus nonpoor, using a given poverty line, identifying the vulnerable nonpoor is of particular relevance for policy. These are households that are above the poverty line and that face an increased risk of slipping into poverty during adverse shocks like the current COVID-19 pandemic. In particular, the “vulnerable” groups are those that fall above the poverty line and below the vulnerability line. The vulnerability line defines a level of consumption that delineates the vulnerable nonpoor from the economically secure (middle class).[3] Once the vulnerable groups are identified, it is possible to explore the peculiar characteristics of these population subgroups. How one defines the vulnerability line is the key question. In this paper, we follow the recent study by Dang and Lanjouw (2017) in defining the vulnerability line using a prespecified vulnerability index. Once we obtain the vulnerability line, it is possible to analyze the poverty dynamics of the three groups: poor, the vulnerable nonpoor, and the economically secure.

Finally, we conduct a validation exercise using the “actual” panel data from the three waves of the Ethiopian socioeconomic surveys (ESSs) conducted in 2011/2012, 2013/2014, and 2015/2016.

This also enables us to compare our results to the poverty dynamics results reported by the World Bank in its poverty assessment reports for Ethiopia and, most important, to draw additional insights that are potentially missing from static poverty analysis, as well as from the analysis of poverty dynamics performed based on smaller panel data sets.

3 | EMPIRICAL RESULTS

In this section, we present the results of poverty dynamics obtained from the synthetic panel data to see how the relative positions of households in the consumption distribution change during the two survey rounds and to understand the factors responsible for the observed change. In particular, in Section 3.1 we first present bound estimates for poverty mobility/immobility using nonparametric and parametric techniques.[4] While the former does not impose any structure on the underlying error distribution, the latter presupposes that the joint distribution of the error terms is bivariate normal. We then present actual point estimates for poverty mobility/immobility following the methodology suggested by Dang and Lanjouw (2013). In Section 3.2, we present results from the profiling exercise to understand the socioeconomic factors that induce changes in the poverty status of households overtime.

3.1 | Poverty dynamics: Evidence from synthetic panel data

3.1.1 | Nonparametric estimates

As observed from Table A1, for the nonparametric approach, we estimate three models by sequentially introducing time-invariant variables related to household and/or household head characteristics.[5] In Model 1, we control for the age, marital status, and education level of the household head, as well as whether the household is located in rural or urban areas. In Models 2 and 3, we sequentially added the gender of the household head and regional fixed effects. In constructing the synthetic panel, we follow the standard practice in the literature, restricting the age of the household head in the first survey round between 25 and 55 years and adjusting accordingly for the following round. Restricting the household head's age in such a way guarantees the stability of the reference population.[6] The 25–55 age range is chosen to minimize the formation of new households and the dissolution of existing ones. Moreover, the lower age limit should be selected such that household heads have generally reached their maximum level of education (Garce´s-Urzainqui et al., 2021).

As observed from Table A1, and focusing on the full model (Model 3), the upper and lower bounds of the nonparametric estimates, respectively, show that 6%–16% of the population in Ethiopia remains poor in both survey rounds. On the contrary, the result shows that up to 24% of the population escapes poverty between the two rounds. Although the estimated bound is a bit too wide, our estimates further show that up to 10% of households are likely to fall into poverty over the two rounds.

3.1.2 | Parametric estimates

In Table 1, we present a bound estimate using a parametric approach, which provides sharper bound estimates of poverty mobility/immobility without the need for a large set of control variables. Therefore, we estimate three models with different values of the correlation coefficient (ρ).

TABLE 1 Poverty dynamics from synthetic panel data: Parametric approach

	Nonparametric	Parametric LB			Parametric UB			Nonparametric
Poverty status	**LB**	**M1**	**M2**	**M3**	**M3**	**M2**	**M1**	**UB**
Poor, poor	15.7	23.4	18.7	17.1	12.0	11.0	8.9	5.7
Poor, nonpoor	7.2	7.2	11.8	13.5	18.5	19.6	21.6	24.3
Nonpoor, poor	0.2	0.4	5.1	6.7	11.8	12.8	14.9	10.2
Nonpoor, nonpoor	76.9	69.0	64.4	62.8	57.7	56.6	54.6	59.8
N	16,186	16,186	16,186	16,186	16,186	16,186	16,186	16,186

Note: LB and UB refer to upper and lower bounds, respectively.

Source: Own computation is based on data from Household Consumption Expenditure surveys from 2010/2011 and 2015/2016. Household head age is restricted to the age category between 25 and 55 years for the first survey round and between 30 and 60 years for the second survey round. Estimates are performed using survey weights.

In particular, we follow Dang et al. (2014) and use values of ρ equal to [1 and 0] (Model 1), [0.8, 0.2] (Model 2), and [0.7, 0.3] (Model 3) for lower and upper bounds, respectively. For comparison, in Table 1, we also include the nonparametric lower- and upper-bound estimates from Table A1 that are performed based on the full model (the second and last columns).[7]

As observed from the results, the upper and lower bounds of the parametric estimates, respectively, show that 12%–17% of the population in Ethiopia remained poor in both survey rounds. On the contrary, 14%–19% of the population managed to escape poverty between the two rounds. Furthermore, the lower and upper bounds of the parametric results, respectively, show that 7%–12% of households are likely to fall into poverty over the two rounds, and this bound is much narrower (as expected) compared to the nonparametric estimates.

3.1.3 | Point estimates

Finally, we present the actual point estimates of the different poverty dynamics (joint and conditional probabilities of moving into and out of poverty) following the methodology suggested by Dang and Lanjouw (2013). While the joint probabilities (Table 2) show the share of households in different poverty status categories considering both survey rounds together, the conditional probabilities (Table 3) show the share of households in different poverty status categories in one period conditional on their poverty status in the other period.

Observing the results of the joint probability estimates, considering both survey rounds together, about 24% of the population is estimated to be chronically poor (remained poor in both periods), and 12% of people who were poor in the first period managed to move out of poverty in the second period. On the contrary, about 7% of the households were nonpoor in the first period but slipped into poverty in the second period. These results on the transitions into and out of poverty show that there is net progress (5 percentage points) in reducing poverty in Ethiopia between the two periods, and this is close to the 6 percentage point decline in the headcount poverty rate officially reported by the government for the same period.

Moving to the results from conditional probability point estimates in Table 3, we can see that there is a high degree of persistence in poverty. In particular, out the total poor in 2010/2011, about 64% of the people who were poor in 2010/2011 remained poor in 2015/2016. A better story emerges when we observe the transition from poor to nonpoor category. That is, the probability of escaping poverty is higher (36%), and this is by far greater compared to the probability that nonpoor households fall into poverty (9%).

TABLE 2 Point estimates of poverty dynamics based on synthetic panel data: Joint probability estimates 2011–2016 (%)

		2016		
	Poverty status	**Poor**	**Nonpoor**	**Total**
2011	Poor	23.7	12.1	35.8
	Nonpoor	5.6	58.6	64.2
	Total	29.3	70.7	100.000
	Observations	16,186		

Source: Own computation based on data from Household Consumption Expenditure surveys of 2010/2011 and 2015/2016. Household head age is restricted to between 25 and 55 years for the first survey round and between 30 and 60 years for the second survey round. Estimates are performed using survey weights.

TABLE 3 Point estimates of poverty dynamics based on synthetic panel data: Conditional probability estimates 2011–2016 (%)

		2016		
	Poverty status	**Poor**	**Nonpoor**	**Total**
2011	Poor	64.0	36.0	100.000
	Nonpoor	9.1	90.9	100.000
	Observations	16,186		

Source: Own computation based on data from Household Consumption Expenditure surveys of 2010/2011 and 2015/2016. Household head age is restricted to between 25 and 55 years for the first survey round and between 30 and 60 years for the second survey round. Estimates are performed using survey weights.

3.1.4 | Identifying the vulnerable nonpoor

Apart from classifying the population into poor versus nonpoor, we further disaggregate the poverty dynamics by identifying the segment of the population that is currently nonpoor but that faces an increased risk of falling into poverty in the future. In particular, we identify the vulnerable nonpoor by defining a vulnerability line following the methodology proposed by Dang and Lanjouw (2017).

According to Dang and Lanjouw (2017), the vulnerability line is determined by first specifying either the "insecurity index"—the probability of falling into poverty in period 2, conditional on being in the middle class in period 1—or the "vulnerability index"—the probability of falling into poverty in period 2 conditional on being vulnerable nonpoor in period 1. Accordingly, here we determine the vulnerability line by taking a vulnerability index of 20%. This results in a vulnerability line of Ethiopian Birr (ETB) 4,410, which roughly amounts to scaling up the 2011 poverty line (ETB 3,781) by 116.64%. This results in 42% of the population remaining below the vulnerability line. The vulnerability line for 2015/2016 (ETB 8,379) is set by deflating the 2010/2011 vulnerability line using the same factor (GDP deflator) used to adjust the 2010/2011 poverty line.

As observed from Table 4, about 24% of the population remains poor in both 2010/2011 and 2015/2016 (chronically poor). Given the share of the population that was poor in 2010/2011 (about 36%), this implies that 66% of the population cannot move out of poverty in 2015/2016. Moreover, from the total vulnerable population in 2010/2011, while 4.5% slipped into poverty, 7.5% and 9.9% stayed vulnerable and moved to the middle class in 2015/2016, respectively. We can see some welfare improvements between 2010/2011 and 2015/2016. In particular, there is 22% upward mobility and 10% downward mobility. While the percentage of the poor shows a 6.4 percentage point (17.9%) decline, the percentage of the middle class has increased by 7.9 percentage points (18.7%). The vulnerable group, on the contrary, does not change much, showing a decline of only 1.4 percentage points from 21.9% of the total population in 2010/2011.

In Table 5, we present conditional probability estimates of vulnerability and poverty dynamics. As observed from this table, there is a high probability of upward transition. In particular, about 24% and 12% of households, respectively, move from the poor to the vulnerable category and the middle-class category in 2015/2016. And a much higher upward mobility is observed for households that move from being vulnerable to the middle class (46.2%). Moreover, there is also a high probability of maintaining middle-class status (85.3%). These positive welfare transitions observed for Ethiopia might be consistent with the high economic growth the country has registered over the past decade.

TABLE 4 Vulnerability and poverty dynamics: Joint probabilities 2011–2016

		2016			
	Poverty status	**Poor**	**Vulnerable**	**Middle class**	**Total**
2011	Poor	23.7	8.3	3.8	35.8
	Vulnerable	4.5	7.5	9.9	21.9
	Middle class	1.1	4.7	36.5	42.3
	Total	29.4	20.5	50.2	100.0
	Observations	16,186			

Source: Own computation based on data from Household Consumption Expenditure surveys of 2010/2011 and 2015/2016. The vulnerability line is calculated by taking a vulnerability index of 20%. This results in a vulnerability line of ETB 4,410. The age of the household head is restricted to between 25 and 55 years for the first survey round and between 30 and 60 years for the second survey round. Estimates are performed using survey weights.

TABLE 5 Vulnerability and poverty dynamics: Conditional probabilities 2011–2016

		2016			
	Poverty status	**Poor**	**Vulnerable**	**Middle class**	**Total**
2011	Poor	64.0	23.8	12.2	100.0
	Vulnerable	20.0	33.8	46.2	100.0
	Middle class	2.8	11.9	85.3	100.0
	Observations	16,186			

Source: Own computation based on data from Household Consumption Expenditure surveys of 2010/2011 and 2015/2016. The vulnerability line is calculated by taking a vulnerability index of 20%. This results in a vulnerability line of ETB 4,410. The age of the household head is restricted to between 25 and 55 years for the first survey round and between 30 and 60 years for the second survey round. Estimates are performed using survey weights.

In the next section, we explore household and household head characteristics that might explain the observed poverty dynamics.

3.2 | Correlates of poverty dynamics

Having identified the poor and the vulnerable nonpoor, the next important step is to profile their socioeconomic characteristics to identify factors associated with poverty transitions or the lack thereof and to assess which section of the society is likely to be highly affected by the adverse impacts of the COVID-19 pandemic. In view of this, we analyze the correlates of poverty dynamics, focusing on poverty persistence and downward mobility, as these transitions are of particular relevance for the analysis in this study. The group of households that experience poverty persistence and downward mobility in the pre-COVID period is likely to be the same group that will be adversely affected by the pandemic.

Figure 1 shows poverty persistence among population groups with different socioeconomic characteristics. The red broken horizontal line shows the average probability of being poor in 2016 conditional on being poor in 2011, which is 64%. While the red triangles on top of the broken line show household or household head characteristics that are associated with an above-average probability of immobility, the probability of staying poor in 2016 conditional on being poor in 2011, the green diamonds below the horizontal line show a below-average probability of immobility.

Interesting insights emerge from this figure. Households where the household head has a secondary or above secondary level of education have a below-average probability of experiencing poverty immobility compared to households where the head has an elementary or below-elementary level of education. Concerning the type of employment of the household head, households where the head is a domestic worker have an extremely high (about 80%) probability of being chronically poor. Households with a self-employed household head also have an above-average probability of remaining poor in 2016 conditional on being poor in 2011. There is also a gender and location difference in poverty immobility: female-headed households and households living in urban areas have a lower-than-average probability of poverty immobility. Finally, studying the sector of engagement, households where the household head works in the agriculture, fishing, or mining sector have an above-average probability of being chronically poor compared to other sectors.

Figure 2 shows probabilities of downward mobility (from vulnerable nonpoor to poor) among population groups with different socioeconomic characteristics. As observed from the figure, household heads who are illiterate or with an elementary-level education have an above-average probability of being poor in 2016 conditional on being vulnerable nonpoor in 2011. When we observe the employment type, households where the head is a domestic worker are extremely likely to be vulnerable to a fall into poverty. In addition, households where the head is employed in associations and is self-employed have a higher probability of becoming poor conditional on being vulnerable in the previous period. Finally, male-headed households; households living in rural areas; and households where the head works in agriculture, mining, and fisheries also have an above-average probability of downward mobility.

The preceding analysis, though informative as to which household and/or household head characteristics determine poverty immobility and downward mobility, has the limitation that some of the population groups may overlap, making it difficult to disentangle the roles of the

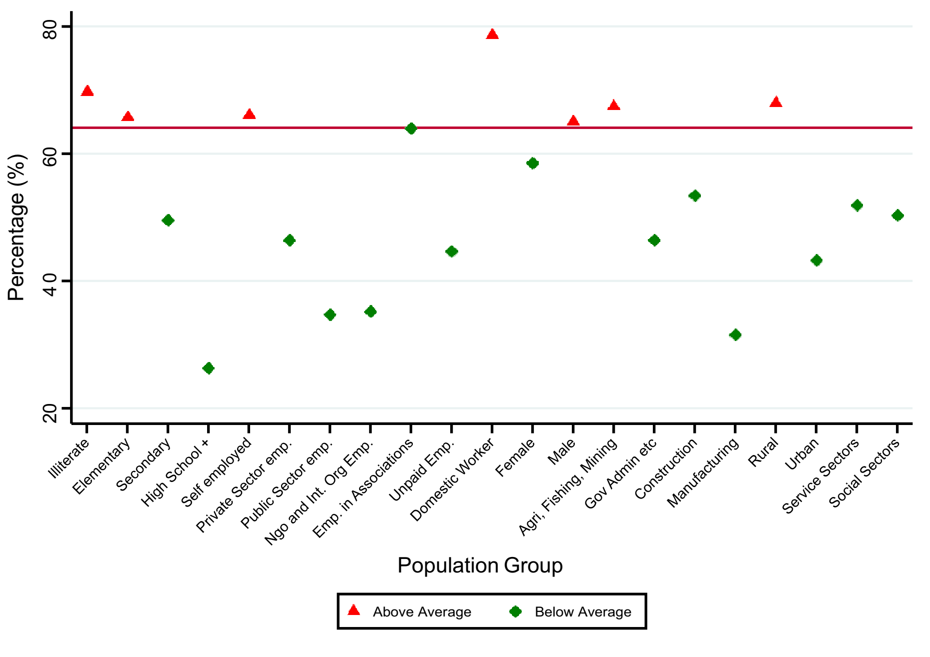

FIGURE 1 Poverty immobility and correlates: 2011 versus 2016. The dashed line represents the average probability of being poor in 2016 conditional on being poor in 2011 [Colour figure can be viewed at wileyonlinelibrary.com]

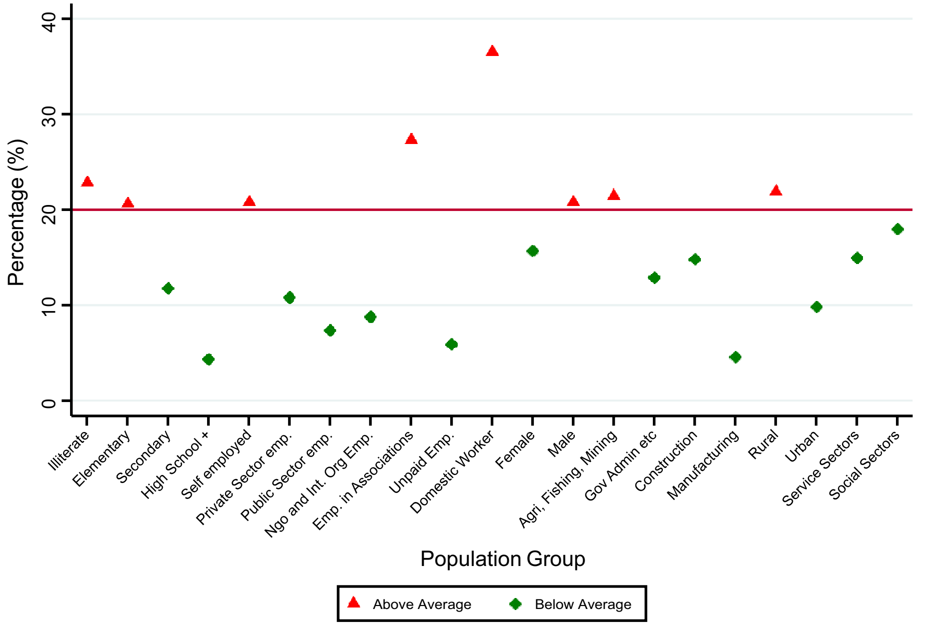

FIGURE 2 Downward mobility and correlates: 2011 versus 2016. The dashed line represents the average probability of being poor in 2016 conditional on being Vulnerable non-poor in 2011 [Colour figure can be viewed at wileyonlinelibrary.com]

different characteristics. For instance, it is important to differentiate the role of the socioeconomic factors that are associated with poverty immobility/downward mobility, vis-à-vis the area of residence—rural versus urban. Thus, we present a more disaggregated poverty profiling to partly address this concern.

3.2.1 | Poverty dynamics by area of residence

As shown in Tables A3 and A4, the poverty rate for rural areas in Ethiopia is much higher than that of urban areas. Here, we investigate the differences in poverty transitions for households living in rural areas compared to urban areas. Therefore, we plot the conditional probabilities of being poor in Figure 3a and vulnerable in Figure 3b by area of residence.

In Figure 3a, we compare the relative share of rural versus urban households that remain in poverty and/or that move into/out of poverty. When we study the degree of immobility, as seen from the light green bars in Figure 3a, we see that rural households are more likely to remain poor (68%) compared to urban households who are 25 percentage points less likely to remain poor in the second period. Studying the probability of escaping poverty, as seen in Figure 3a, the probability that the poor will become vulnerable is 7.78 percentage points higher in urban compared to rural areas. Moreover, the probability that the poor move to the middle class is higher for urban (26.4%) compared to rural households, who are almost 17 percentage points less likely to move into the middle class.

In Figure 3b, we compare the probabilities of falling into and out of poverty for rural and urban households. As observed in Figure 3b, we see that there is a high probability of falling into poverty for the vulnerable nonpoor, and this probability is higher in rural areas (21.9%) compared

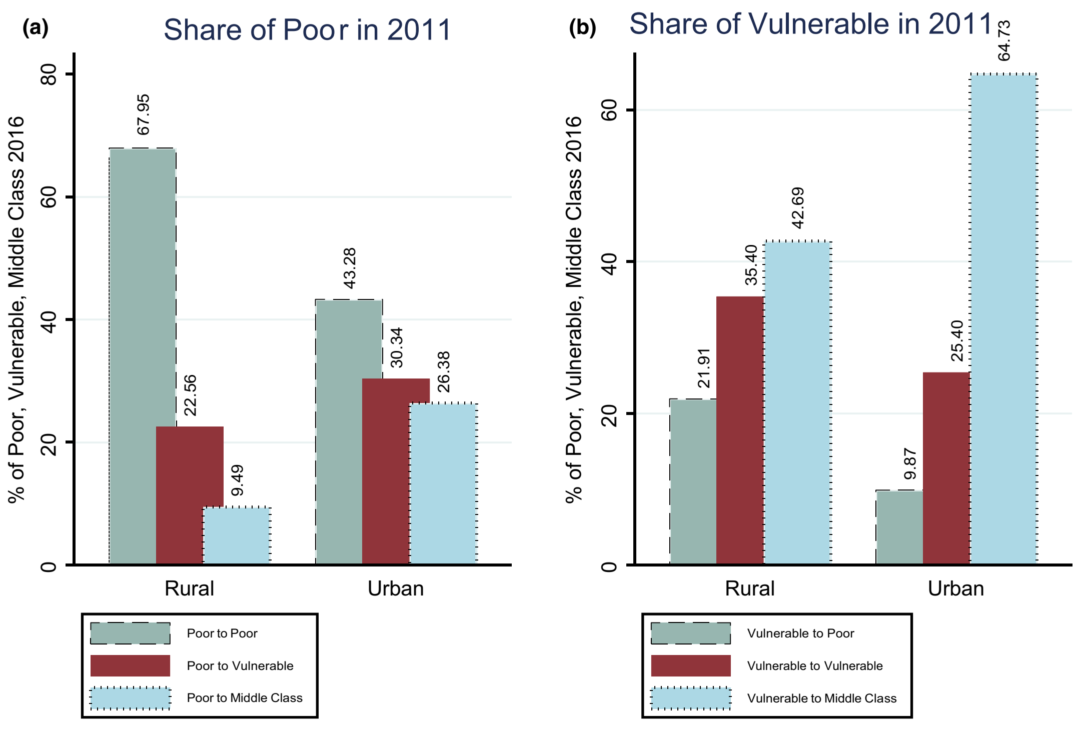

FIGURE 3 Poverty dynamics by area of residence: 2011–2016. *Source*: Author's computation based on the HCE survey data [Colour figure can be viewed at wileyonlinelibrary.com]

to urban areas (9.9%). Moreover, the probability of transitioning out of the vulnerable group to the middle class is higher for those in urban areas compared to rural areas.

3.2.2 | Poverty dynamics by gender of the household head

In Figure 4, we compare the poverty dynamics of female- and male-headed households living in rural and urban areas. As observed in Figure 4a, the degree of immobility is quite high for both female- and male-headed households in rural areas (64% and 69% for women and men, respectively) compared to urban areas (about 43% and 44%, respectively, for women and men). On the contrary, the probability of escaping poverty (poor to vulnerable and poor to middle class) is relatively low for both female- and male-headed households in rural areas compared to their urban counterparts. Finally, as observed in Figure 4b, rural vulnerable nonpoor female- and male-headed households have a relatively higher (lower) probability of transitioning into poverty (middle-class) status compared to urban female- and male-headed vulnerable households.

3.2.3 | Poverty dynamics by education status of the household head

Figure 5 shows poverty dynamics by categorizing households based on the educational status of the household head and area of residence. As observed in Figure 5a, poverty persistence

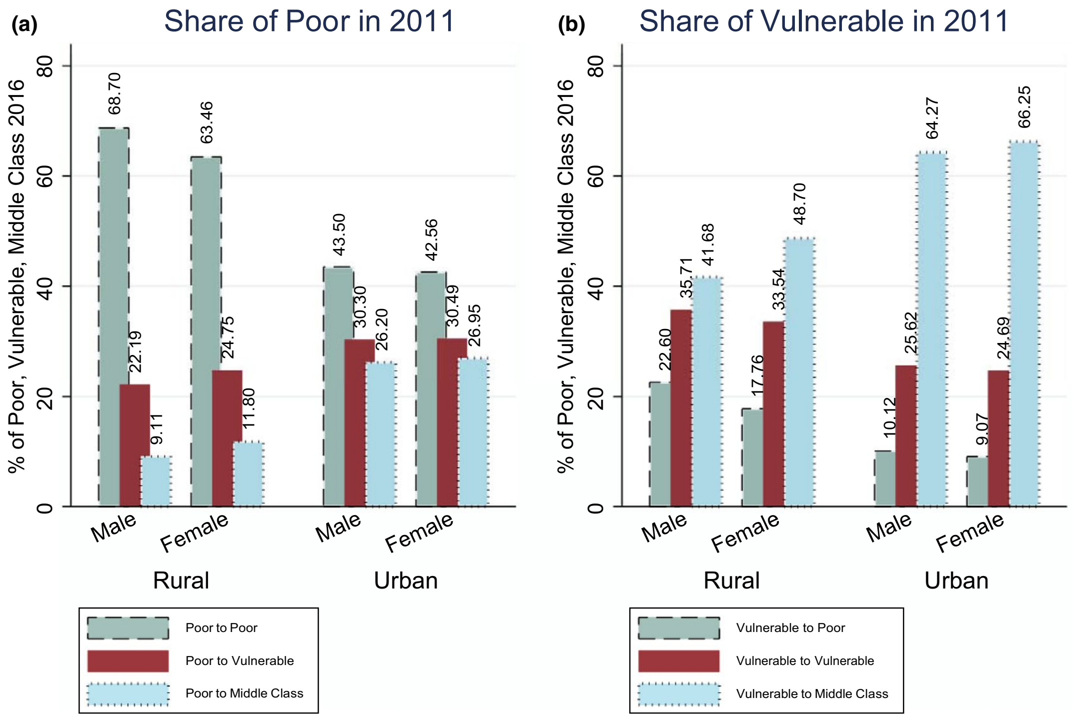

FIGURE 4 Poverty dynamics by gender of the household head: 2011–2016. *Source*: Author's computation based on the HCE survey data [Colour figure can be viewed at wileyonlinelibrary.com]

decreases with an increase in the level of education of the head. Regardless of whether the household resides in an urban or rural area, households with a high school and above high school level of education have, respectively, 16–20 and 39–43 percentage points lower probability of remaining poor compared to households where the head has an elementary or lower level of education. As observed in Figure 5a, households with highly educated household heads have a higher (42%) probability of transitioning into middle-class status.

Finally, Figure 5b shows that vulnerable households where the head is highly educated have a higher (lower) probability of moving into the middle class (poverty) compared to vulnerable households where the head has an elementary or lower level of education. This signifies the important role of education in the country's efforts to reduce poverty.[8]

3.2.4 | Poverty dynamics by type of employment of the household head

Figure 6 presents the probabilities of moving out of poverty based on the type of employment of the household head. As observed in Figure 6a, households where the head is a domestic worker have the highest probability (about 79%) of remaining poor in both periods and the lowest probability of escaping poverty. This is followed by households where the head is self-employed and employed in associations. Similarly, from Figure 6b, we see that domestic workers have the highest probability of downward mobility, followed by the self-employed and those employed in associations.

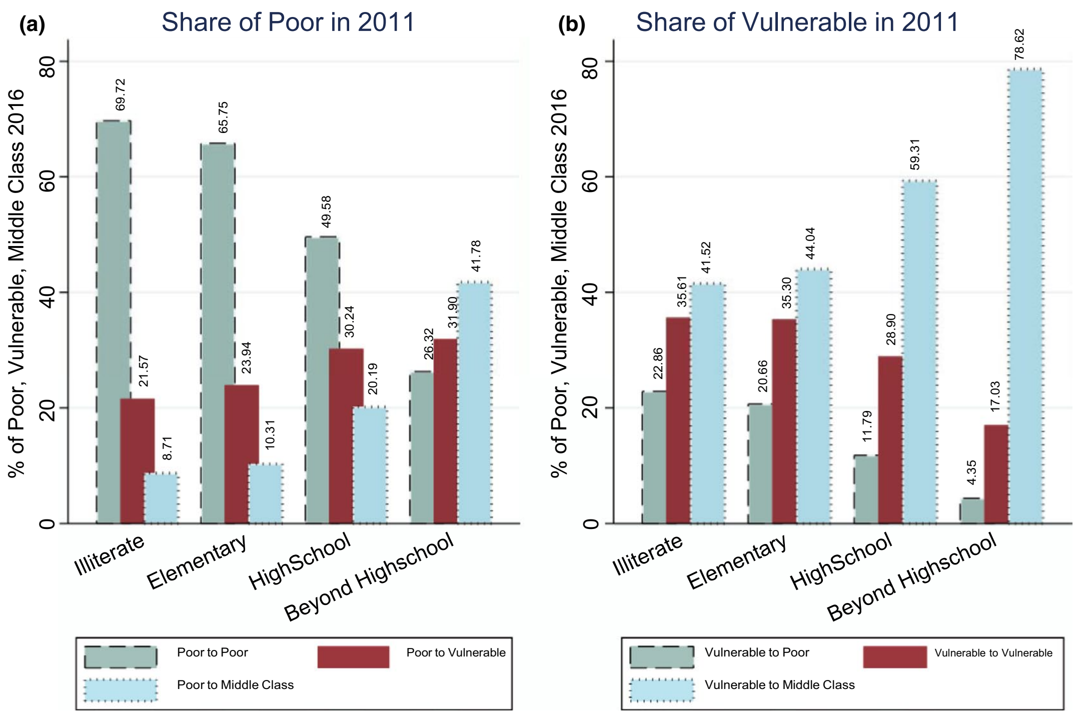

FIGURE 5 Poverty dynamics by the educational status of the household head: 2011–2016. *Source*: Author's computation based on the HCE survey data [Colour figure can be viewed at wileyonlinelibrary.com]

3.2.5 | Poverty dynamics by sector of engagement of the household head

Figure 7 shows some level of heterogeneity in household poverty dynamics based on the sector of engagement of the household head. As observed in Figure 7a, poor households where the head is engaged in the agricultural and service sectors, like hotels and restaurants, transport, construction, and wholesale and maintenance, have the highest probabilities of poverty persistence. This can partly be explained by the low skill levels and relatively high share of informality observed in these sectors. Similarly, Figure 7b shows that households with heads engaged in the aforementioned sectors have a higher probability of downward mobility and a lower probability of moving to the middle class.

3.2.6 | Poverty dynamics by region

Figure 8 compares the probabilities of remaining in poverty and/or transitioning out of poverty across the different regions of Ethiopia. It can be observed that the largely urban Dire Dawa and Addis Ababa city administrations, Harari region, as well as the arable land-rich region of Gambella, have a relatively lower probability of poverty persistence. Figure 8b shows that these regions fare better in terms of probabilities of moving out of poverty. On the contrary, the arid, drought-prone Somali and Afar regions, as well as the Amhara region, have the lowest probability of transitioning out of poverty (see Figure 8a). Consistent with official figures, the Amhara region is among the worst-performing regions in the country, probably due to the high population

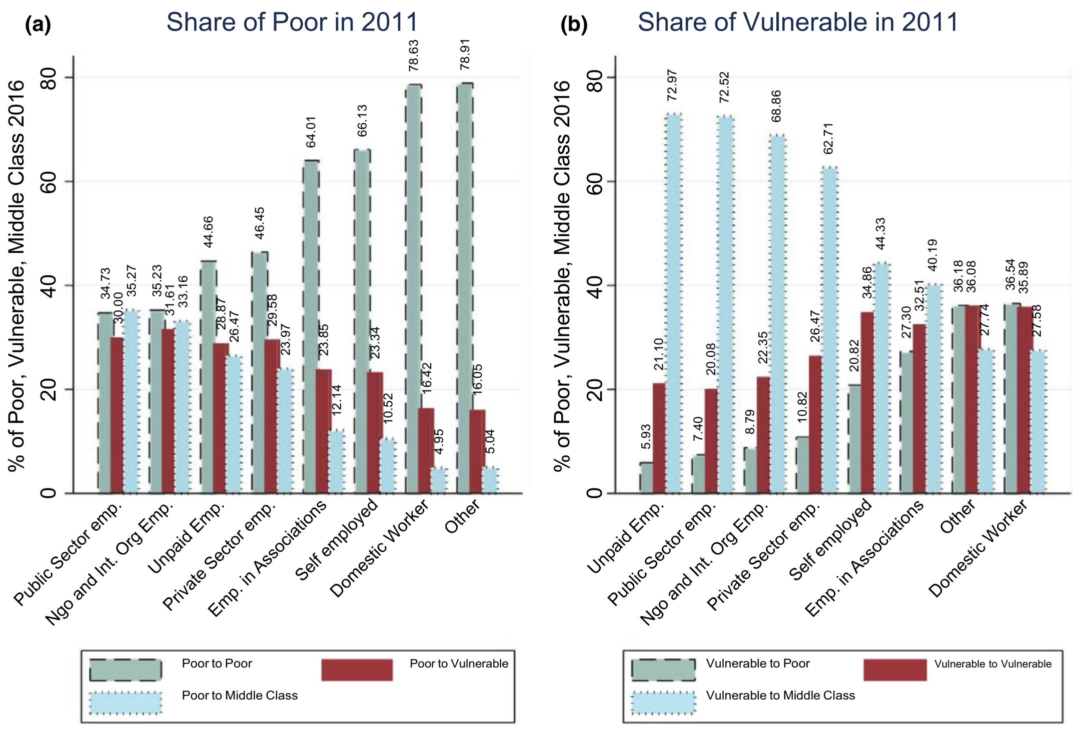

FIGURE 6 Poverty dynamics by type employment of the household head: 2011–2016. *Source*: Author's computation based on the HCE survey data [Colour figure can be viewed at wileyonlinelibrary.com]

density and highly degraded land, together with small per-capita land-holding, observed in the region.

3.3 | Validating the synthetic panel data approach

To test the validity of the synthetic panel data approach, we have used the two rounds of the actual panel data from the ESSs. Following Dang et al. (2014) we construct synthetic panel data by taking a random subsample of 50% of the observations from each round of the ESS data. Since using the same poverty line as the one used with the HCE survey data results in starkly different poverty rates, we have used different poverty lines for the ESS subsamples. In particular, for 2013/2014, we have used a poverty line of ETB 2,336.73, by using the 30th percentile of real consumption expenditure, given in 2011 prices.

The poverty line calculated in this method is smaller than the national poverty line (ETB 3,781) that is given in December 2010 prices but results in a headcount poverty rate of 29%. This looks reasonable given the 2011 official headcount poverty rate of 29.6% calculated using the HCE data set. Similarly, for 2015/2016, we have used a poverty line of ETB 2,367.87 by taking the 30th percentile of real consumption expenditure, which is given in 2011 prices. Although the poverty line calculated in this method is smaller than the ETB 3,781 in 2011 prices, it results in a headcount poverty rate of 28%. This is reasonable given the 2016 official headcount poverty rate of 23.5% calculated from the HCE survey.

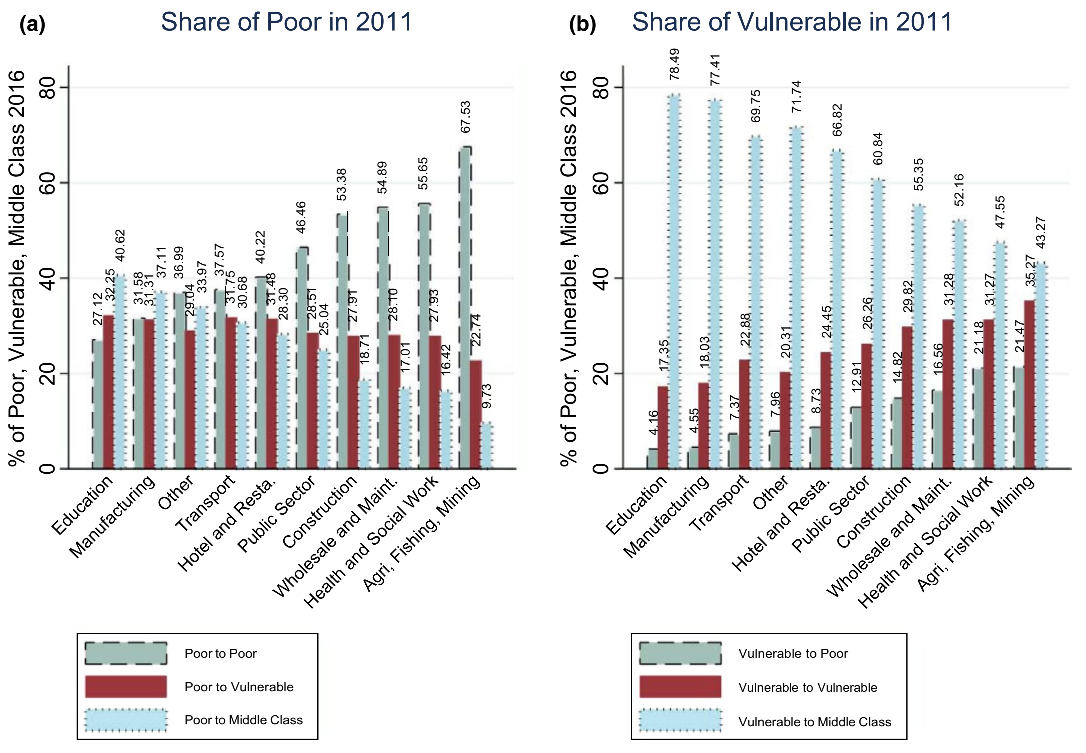

FIGURE 7 Poverty dynamics by the sector of engagement of the household head: 2011–2016. *Source*: Author's computation based on the HCE survey data [Colour figure can be viewed at wileyonlinelibrary.com]

The results from the synthetic panel data are then compared to the estimates performed using the real panel data. We estimate the poverty dynamics between 2013/2014 and 2015/2016 using both the nonparametric and parametric bound approaches. As observed from the estimates provided in Table A5, in each case, the estimates found from the real panel data set fall between the upper and lower bounds calculated based on the synthetic panel data approach. This indicates that the larger nationally and regionally representative repeated cross-sectional data set from the HCE survey can be used to generate reliable estimates of poverty dynamics by applying a synthetic panel data technique.

4 | COVID-19 AND ITS IMPLICATION FOR VULNERABILITY IN Ethiopia

4.1 | COVID-19 in Ethiopia: Stylized facts

In this section, after providing a view of the COVID-19 situation in Ethiopia, we assess the emerging and unfolding evidence on the socioeconomic impact of the pandemic to set the scene for the discussion in the next section on the likely impact of COVID-19 on poverty and vulnerability in Ethiopia.

The first case of coronavirus was reported in Ethiopia on March 13, 2020, and since then the number of active cases has continued to increase. According to the Ethiopian Public Health Institute, as of January 17, 2021, the total number of COVID-19 confirmed cases and deaths,

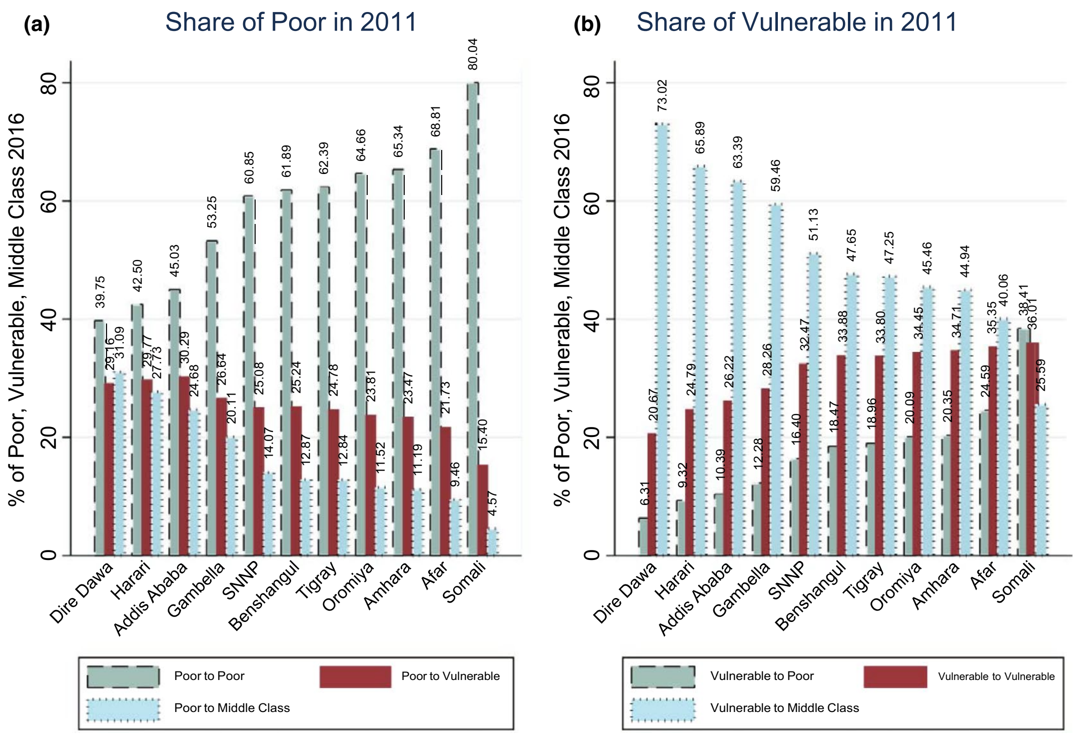

FIGURE 8 Poverty dynamics by region: 2011–2016. *Source*: Author's computation based on the HCE survey data [Colour figure can be viewed at wileyonlinelibrary.com]

respectively, reached 131,195 and 2,030.8. Regarding the geographic distribution of the spread of the pandemic, Figure A1 shows that more than 57% of the total reported cases are in Addis Ababa, followed by Oromia (16%), Tigray (5%), and Amhara (5%).

Though COVID-19 is a transitory shock, it is likely to have an adverse long-term impact on the socioeconomic well-being of households, through both its direct impact on health and its indirect impact following the various containment measures implemented by the government to control the spread of the virus. The impact on households can occur through various channels, including the impact on labor income and nonlabor income (domestic and international remittances, private and public transfers) and the direct impact on consumption (due to increases in food prices and supply disruptions for imported items) and service disruptions (health system saturation, suspension of classes and feeding programs) (World Bank, 2020c). These are likely to induce a slowdown in economic growth and poverty reduction. The following text assesses the current evidence in this regard.

Various studies have tried to quantify the likely impact of COVID-19 on economic growth performance in Ethiopia under different scenarios, including the severity of the shock, the ongoing developments in the global economy, and the duration of the pandemic. See, for instance, Cancedda et al. (2020), United Nations (2020), IMF (2020), Beyene et al. (2020), and Goshu et al. (2020). The findings from these studies point to slow growth and recovery in the post-COVID years.

Regarding the impact of the pandemic on poverty, the unprecedented socioeconomic impact is likely to reverse the hard-won poverty reduction gains achieved in the past years. The emerging evidence seems to confirm this. For instance, United Nations (2020), based on estimates from the United Nations Economic Commission for Africa, outlines three different scenarios regarding the expected decrease in GDP growth after the pandemic and its likely impact on poverty. According to the report, assuming a growth-poverty elasticity of −0.22 and a worst-case scenario of a 4.5% decrease in GDP, income poverty is expected to increase by 2.2 million people.

The report adds that the poverty effects under different growth scenarios are due to loss of income mainly in the informal sector. Moreover, according to the assessment made by the United Nations Children's Fund (UNICEF), from 400,000 to 1.2 million more people, about 50% of whom are children, would fall below the poverty line (UNICEF, 2020). These numbers, though speculative and possibly subject to change depending on how the socioeconomic impacts of the pandemic evolve, are clear manifestations of how income disruptions from adverse shocks like the current pandemic can easily change the poverty status of millions.[9]

In general, even if the poverty reduction achievements Ethiopia has registered so far are encouraging, the vulnerability in the country remains quite high. According to Bundervoet and Finn (2020), during the period 2012–2016, close to half of people in rural areas and small towns experienced at least one spell of poverty, meaning they were below the poverty line at some point during this period. The high level of vulnerability means that a considerable share of households are at risk of falling into poverty during an adverse income shock, like the one induced by COVID-19.

4.2 | Likely impact of COVID-19 on poverty dynamics in Ethiopia: By economic sector, geographic areas, employment types, and population segments

This section is devoted to assessing the likely impact of COVID-19 on poverty dynamics in Ethiopia. In particular, a key question to be answered here is which section of the society is likely to be dragged into poverty during the COVID-19 pandemic. As we do not yet have data/information on our outcome of interest in the post-crisis period, at this stage we will not be able to directly assess and quantify the impact of the COVID crisis on poverty/vulnerability empirically. However, one can use the insights from the poverty dynamics and vulnerability analysis based on the pre-COVID crisis data to assess the likely impact of the pandemic on poverty and to see which areas/groups/sectors will likely be disproportionately affected. Thus, our aim at this stage is not to provide a full-fledged assessment of the impact of the COVID-19 crisis on poverty but rather to conduct an initial speculative assessment to identify emerging priorities for public policy action.

4.2.1 | Economic sectors

Our poverty dynamics and vulnerability analysis using pre-COVID data and discussion in Section 3.2 shows that poor households where the head is engaged in the primary sector (agriculture, mining, and fisheries) and service sector (hotels and restaurants, transport, construction, and wholesale and maintenance) have the highest probabilities of poverty persistence, as well as downward mobility. When we observe the emerging evidence in the literature regarding the impact of COVID-19 in Ethiopia, most of these sectors are found to be heavily hit by the corona pandemic. For instance, Weiser et al. (2020) used a high-frequency phone survey, conducted by the World Bank, to assess the impact of COVID-19. These authors found that hospitality, construction, and wholesale and retail were the most affected, accounting for 38%, 33%, and 31% of the job losses reported by the respondents, respectively. Similarly, Cancedda et al. (2020) identified transport, retail sales, entertainment, tourism, and personal services as the main sectors of economic activity that are immediately affected by containment measures and therefore experience the earliest and largest impact of the pandemic. On the contrary, in the case of agriculture, even if the sector is characterized by high poverty persistence and downward mobility, both the aforementioned studies show that agriculture is among the least affected sectors.

Overall, since most of the sectors that are hardest hit by the corona pandemic are also characterized by higher downward and lower upward mobility, the pandemic is likely to have a severe impact on poverty. Unless the government, together with development partners, identifies the most vulnerable sectors and takes corrective measures, the pandemic is likely to reverse the gain in poverty reduction achieved in the past years.

4.2.2 | Geographic areas: Rural versus urban

Studies show that the effect of the pandemic is likely to be greater among urban households. The disproportional impact on urban areas is mainly because the high population density in urban areas aggravates the spread of the pandemic. Apart from the health impact, the COVID-induced income shock is biased toward urban areas as services and businesses (both formal and informal) that are hard-hit by the pandemic are mostly concentrated in urban areas. For instance, according to Weiser et al. (2020), 13% of respondents in the World Bank's high-frequency phone survey had lost their jobs since the outbreak of COVID-19, and of these, 18% were from urban areas and 10% from rural areas. As a result, the gain in urban poverty reduction observed in recent years in Ethiopia is likely to be jeopardized by the adverse impact of the pandemic.

Moreover, as observed from evidence using pre-COVID data, the probability of remaining poor and moving from vulnerable nonpoor to poor in urban areas is 43% and 10%, respectively. This, together with the fact that the impact of the pandemic is biased toward urban areas, implies that the pandemic is likely to increase urban poverty. This accentuates the need for policy intervention directed at mitigating the adverse impacts of the pandemic in urban areas. However, this is not to suggest a shift in policy focus from rural to urban areas. Although not as much as urban areas, rural areas are also affected by the pandemic, particularly rural areas that are connected to urban markets. Moreover, the COVID-induced deceleration of activities in urban areas and the likely increase in urban poverty will also have implications for rural poverty, for instance, by inducing a decline in domestic transfer from urban to rural areas (see Bundervoet & Finn, 2020, and Cancedda et al., 2020). Furthermore, as the evidence from the pre-COVID data shows, the probability of moving from vulnerable nonpoor to poor is 12 percentage points higher in rural areas compared to urban areas. This evidence, coupled with the fact that poverty is largely a rural phenomenon in Ethiopia, as discussed in the Introduction, implies that the post-COVID policy focus should not solely be on urban areas.

4.2.3 | Employment types

The poverty dynamics analysis using the pre-COVID data shows that households where the head is a domestic worker have the highest probability of poverty persistence and downward mobility. Simultaneously, the emerging evidence on the impact of COVID-19 indicates that domestic workers are among the groups that are most affected by the pandemic (Amdeselassie et al., 2020). In addition, the pre-COVID evidence shows that the self-employed are characterized by high poverty persistence and downward mobility. Early evidence on the impact of the pandemic reveals that self-employed workers, particularly in urban areas, are highly affected by the containment measures taken by the government. Overall, the aforementioned facts show that the current pandemic is likely to increase poverty and vulnerability in Ethiopia by affecting domestic workers and the self-employed.

4.2.4 | Population segments

The impact of the pandemic is likely to be heterogeneous across different population segments. For instance, according to the assessment of the United Nations (2020), groups that are most affected by the coronavirus pandemic in Ethiopia include employees in the urban informal sector, especially women; industrial park employees; pastoralists; frontline health system workers; children of school-going age from households that are poor and food insecure; vulnerable children and adolescents; groups with specific vulnerabilities (persons living with HIV/Aids, persons with disabilities, older persons, the homeless); internally displaced people; returnees/relocatees; and returning migrants and refugees.

In particular, in urban areas where the effect of the pandemic is more pronounced, studies show that women and workers in the informal sector are quite vulnerable/have an increased risk of experiencing an adverse impact from the pandemic. For instance, in three of the most affected sectors, women constitute more than 80% of the workforce (74% in tourism, 80% in the rapidly growing textile and garment industry, and 85% in the floriculture industry) (Cancedda et al., 2020). Given that vulnerable female-headed urban households have a high poverty persistence rate (45%), as discussed in Section 3.2, these facts imply that the pandemic will have a relatively severe impact on the welfare of women in urban areas.

Overall, even if we cannot directly quantify the impact of COVID-19 on poverty in Ethiopia, the preceding assessment clearly shows that the pandemic is likely to have a visible adverse impact on poverty reduction efforts in Ethiopia, particularly urban poverty, as it directly affects factors that are identified as drivers of urban poverty.

5 | CONCLUSION

Poverty eradication through broad-based and sustained economic growth is the core development objective of the Ethiopian government, and most of the country's development plans and strategies are aligned with this objective. Therefore, since the beginning of the 2000s, the government of Ethiopia has designed and implemented various national development plans and strategies with a particular focus on poverty reduction. In line with these efforts, Ethiopia has made visible progress in reducing poverty. For instance, during the sample period covered in the current study (2010/2011–2015/2016), the proportion of people living below the national poverty line decreased by 21%, from 29.6% to 23.5%. Following this decline in the incidence of poverty, 5.3 million people were able to get out of poverty between 2010/2011 and 2015/2016.

Sustaining the aforementioned achievements during unanticipated shocks like the current coronavirus pandemic and the recent internal conflicts mainly in Tigray and the neighboring regions is a major development challenge. Such adverse shocks are likely to induce changes in the poverty status of households over time.

In this scenario, the main aim of this paper was to identify vulnerable groups that face a higher risk of falling into poverty due to COVID-19. Therefore, we undertook a detailed analysis of poverty and vulnerability transitions based on pre-COVID data and conducted profiling of the socioeconomic characteristics of different population segments. The specific aim was to establish which factors are associated with poverty transitions, or lack thereof, and therefore to assess which sections of society are likely to be highly affected by the adverse impacts of the COVID-19 pandemic.

Our results show that there is a high rate of poverty persistence in Ethiopia. About 64% of the total poor population in 2011 remained poor in 2016. On the positive side, there has also been a significant rate of upward mobility in Ethiopia during the sample period; 36% of the poor in 2011 became nonpoor in 2016, of whom 24% became vulnerable nonpoor and 12% moved to middle-class status in 2016. Moreover, the poverty profiling exercise shows a relatively larger upward mobility for urban households and households where the head is relatively more educated; works in nongovernmental organizations, international organizations, and the public sector; and is engaged in the social and manufacturing sectors. Similarly, a relatively large rate of downward mobility is observed for rural households, as well as households where the head is less educated, is self-employed, works as a domestic worker, and is engaged in the primary and service sectors.

As the emerging evidence on the socioeconomic impact of COVID shows, these segments of the population are also the ones that are relatively more affected by the pandemic. Overall, even if we cannot quantify the impact of COVID on poverty mobility/immobility at this stage, it is likely that the pandemic will induce a serious setback in the progress made in poverty reduction by particularly affecting the aforementioned sections of the population.

Finally, the existing evidence on the socioeconomic impact of COVID also shows that the impact of the pandemic is biased toward urban areas. Moreover, the evidence using the pre-COVID data in this study shows that the probability of moving from vulnerable nonpoor to poor status in urban areas is 10%. This implies that the adverse impact of the pandemic is likely to be high in urban areas, and the COVID-induced income shock is likely to increase urban poverty.

These findings accentuate the need for policy intervention to mitigate the adverse impacts of the pandemic in urban areas. However, this is not to suggest a shift in policy focus from rural to urban areas. Although not as much as urban areas, rural areas are also affected by the pandemic, particularly rural areas connected to urban markets. Moreover, the COVID-induced deceleration of activities in urban areas and the likely increase in urban poverty will have implications for rural poverty—for instance, by inducing a decline in domestic transfers from urban to rural areas (see Bundervoet & Finn, 2020, and Cancedda et al., 2020).

In addition, as the evidence from the pre-COVID data shows, the probability of moving from vulnerable nonpoor to poor is 12 percentage points higher in rural areas compared to urban areas. This evidence, coupled with the fact that poverty is largely a rural phenomenon in Ethiopia, implies the post-COVID policy focus on urban areas should not be at the expense of the rural poor.

Concisely, the observed persistence of poverty and the greater risk of falling into poverty even in the normal (pre-COVID) period where the economic growth rate was above 9% are alarming. Poverty persistence and downward mobility (moving from vulnerable nonpoor to poor status) are likely to be aggravated during the current pandemic.

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CONFLICT OF INTEREST

The authors have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the Central Statistics Authority (CSA) of Ethiopia. Data are available from the corresponding author on reasonable request and with the permission of the CSA of Ethiopia.

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ENDNOTES

1 The Ethiopian Socio-Economic Surveys (ESS) data is not chosen as the basis for our main analysis of poverty dynamics for the following reasons: i) ESS which is available for 2011/12, 2013/14 and 2015/16, is nationally representative only for the last two waves as the first round (2011/12) covers rural areas and small towns only; ii) Even if the last two waves are nationally representative, they are not sub-nationally representative for all regions; iii) Moreover, the sample size of ESS is by far smaller, compared to HCE survey.

2 We have excluded the earlier waves in our analysis as there is a huge time gap between the old waves and the recent waves. As a result, the underlying population sampled is likely to have changed, for various reasons, including births, deaths, migration, or natural disasters. This will likely lead to the violation of one of the key assumptions needed in constructing the synthetic panel (see Dang et al., 2014).

3 Following Dang and Lanjouw (2017), we define the middle class as a population group that has a level of consumption above the vulnerability line and therefore is neither poor nor vulnerable.

4 The detailed steps in the nonparametric estimation can be found in Dang et al. (2014, pp. 115–116).

5 The mean comparison of the variables between the two survey rounds is reported in Table A2.

6 This makes it more likely to satisfy one of the key assumptions needed for estimating bounds on poverty transitions; that is, the underlying population being sampled in survey rounds 1 and 2 is the same.

7 In Table 1, Models 1–3 differ based on the values of ρ used in the estimation, while in Table A1, Models 1–3 differ based on the controls included in the estimation.

8 Here it is worth pointing out that there could be a selection issue and other confounding factors, like ability, that might partly explain the result.

9 For instance, World Bank (2020b), in its report on poverty and shared prosperity, provided an estimate, which suggested that COVID-19 could possibly bring 88–115 million people into extreme poverty in 2020, putting the poverty reduction effort back by 3 years. See also Sumner et al. (2020), Mahler et al. (2020), and Vos et al. (2020).

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APPENDIX A

TABLE A1 Poverty dynamics from synthetic panel data

	Nonparametric lower bound			Nonparametric upper bound		
Poverty status	**Model 1**	**Model 2**	**Model 3**	**Model 3**	**Model 2**	**Model 1**
Poor, poor	15.90	15.90	15.70	5.70	5.60	5.60
Poor, nonpoor	7.60	6.00	7.20	24.30	23.50	25.50
Nonpoor, poor	0.00	0.10	0.20	10.20	10.40	10.30
Nonpoor, nonpoor	76.50	78.10	76.90	59.80	60.50	58.60
$_R 2$	0.13	0.25	0.27			
N	18,573.00	16,504.00	16,186.00	16,186.00	16,504.00	18,573.00

Notes: As synthetic panel bounds are defined with reference to mobility, the upper-bound estimates show maximum mobility (Dang et al., 2014). Thus, while the upper-bound estimates correspond to higher probabilities in the case of transitions (poor–non-poor and nonpoor–poor), they are associated with lower probabilities for immobility (poor–poor and nonpoor–nonpoor) (see Garce´s-Urzainqui et al., 2021).

Source: Own computation based on data from Household Consumption Expenditure surveys of 2010/2011 and 2015/2016. Household head age is restricted to between 25 and 55 years for the first survey round and between 30 and 60 years for the second survey round. Estimates are performed using population weights for the respective survey rounds. We have used 500 replications for the estimates.

TABLE A2 Mean comparison between surveys in 2011 and 2016

	Survey year 2011		Survey year 2016		Difference	
Variables	**Observations**	**Mean**	**Observations**	**Mean**	**Mean**	***p*-Value**
Log real consumption	19,308	8.472	18,573	9.190	0.718	0.000
Household size	19,308	6.092	18,573	6.213	0.121	0.025
Place of residence	19,308	0.163	18,573	0.175	0.013	0.284
Age of head	19,308	39.506	18,573	43.168	3.662	0.000
Female-headed household	19,308	0.168	18,573	0.185	0.017	0.013
Head is married	19,308	0.864	18,573	0.866	0.003	0.640
Head is literate	19,308	0.468	18,573	0.462	−0.007	0.606
Head's highest grade completed	18,920	2.792	18,463	2.954	0.162	0.143
Head has disability	19,308	0.001	18,573	0.002	0.001	0.042

Source: Own computation based on data from Household Consumption Expenditure surveys from 2010/2011 and 2015/2016. Household head age is restricted to between 25 and 55 years for the first survey round and between 30 and 60 years for the second survey round. Estimates are performed using survey weights.

TABLE A3 National and regional headcount poverty rates for 2011 and 2016: Unrestricted sample

	Survey year 2011		Survey year 2016	
Regions	**Headcount poverty rate**	**SE**	**Headcount poverty rate**	**SE**
Tigray	0.325	0.024	0.261	0.026
Afara	0.335	0.058	0.242	0.022
Amahara	0.320	0.021	0.266	0.018
Oromiya	0.277	0.017	0.228	0.014
Somali	0.346	0.057	0.233	0.027
Benshangul	0.285	0.048	0.256	0.030
SNNP	0.308	0.021	0.206	0.018
Gambella	0.313	0.024	0.232	0.040
Harari	0.139	0.012	0.081	0.019
Addis Ababa	0.264	0.015	0.158	0.015
Dire Dawa	0.267	0.039	0.166	0.024
Urban	0.214	0.007	0.145	0.007
Rural	0.315	0.012	0.252	0.010
National	0.298	0.010	0.232	0.008

SE, standard error.

Source: Own computation based on data from Household Consumption Expenditure surveys of 2010/2011 and 2015/2016. Estimates are performed using survey weights.

TABLE A4 National and regional headcount poverty rates for 2011 and 2016: Restricted sample

	Survey year 2011		Survey year 2016	
Regions	**Headcount poverty rate**	**SE**	**Headcount poverty rate**	**SE**
Tigray	0.336	0.030	0.290	0.027
Afara	0.321	0.048	0.273	0.023
Amahara	0.323	0.021	0.293	0.017
Oromiya	0.280	0.015	0.258	0.011
Somali	0.334	0.078	0.253	0.018
Benshangul	0.287	0.018	0.284	0.028
SNNP	0.316	0.012	0.235	0.023
Gambella	0.322	0.029	0.258	0.037
Harari	0.152	0.015	0.103	0.026
Addis Ababa	0.232	0.017	0.175	0.016
Dire Dawa	0.268	0.037	0.199	0.028
Urban	0.205	0.007	0.167	0.007
Rural	0.320	0.012	0.280	0.011
National	0.301	0.011	0.260	0.009

SE, standard error.

Source: Own computation based on data from Household Consumption Expenditure surveys of 2010/2011 and 2015/2016. Household head age is restricted to between 25 and 55 years for the first survey round and between 30 and 60 years for the second survey round. Estimates are performed using survey weights.

TABLE A5 Poverty dynamics from synthetic panel data: Validation using parametric approach

Poverty status	Nonparametric LB	Parametric LB M1	Parametric LB M2	Parametric LB M3	Truth	Parametric UP M3	Parametric UP M2	Parametric UP M1	Nonparametric UP
Poor, poor	15.9	18.4	13.9	12.5	8.9 0.0	8.1	7.1	5.5	4.5
Poor, nonpoor	6.6	5.6	10.0	11.5	11.6 0.0	15.9	16.8	18.5	16.8
Nonpoor, poor	0.4	0.5	4.9	6.4	7.1 0.0	10.8	11.7	13.4	11.7
Nonpoor, nonpoor	77.1	75.6	71.2	69.7	72.4 0.0	65.3	64.4	62.7	67.0
N	855.0	855.0	855.0	855.0	3,154.0	855.0	855.0	855.0	855.0

Note: LB and UB, respectively, refer to lower- and upper-bound estimates.

Source: Own computation based on data from Ethiopian socioeconomic surveys of 2013/2014 and 2015/2016. Household head age is restricted to between 25 and 55 years for the first survey round and between 27 and 57 years for the second survey round. Estimates are performed using survey weights.

TABLE A6 Summary statistics

	2011		2016	
	Number of observations	**Mean**	**Number of observations**	**Mean**
National				
Real expenditure per adult equivalent	27,835	7,969.41	30,229	18,877.06
Real food expenditure per adult equivalent	27,835	3,025.41	30,229	9,245.65
Real nonfood expenditure per adult equivalent	27,835	4,944.00	30,229	9,631.41
Real expenditure per capita	27,835	8,073.91	30,229	16,693.83
Real food expenditure per capita	27,835	2,763.82	30,229	7,973.80
Real nonfood expenditure per capita	27,835	5,310.09	30,229	8,720.03
Urban				
Real expenditure per adult equivalent	17,513	9,244.89	19,861	21,956.52
Real food expenditure per adult equivalent	17,513	3,403.47	19,861	10,358.19
Real nonfood expenditure per adult equivalent	17,513	5,841.41	19,861	11,598.32
Real expenditure per capita	17,513	10,283.52	19,861	20,392.89
Real food expenditure per capita	17,513	3,277.70	19,861	9,319.94
Real nonfood expenditure per capita	17,513	7,005.82	19,861	11,072.94
Rural				
Real expenditure per adult equivalent	10,322	5,805.34	10,368	12,978.02
Real food expenditure per adult equivalent	10,322	2,383.96	10,368	7,114.45
Real nonfood expenditure per adult equivalent	10,322	3,421.38	10,368	5,863.57
Real expenditure per capita	10,322	4,324.94	10,368	9,607.90
Real food expenditure per capita	10,322	1,891.93	10,368	5,395.13
Real nonfood expenditure per capita	10,322	2,433.01	10,368	4,212.78

Source: Own computation based on Household Consumption Expenditure survey data, for 2011 and 2016.

TABLE A7 Household consumption regression models: Used for parameter estimation

	2011			2016		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Urban	0.342	0.108	0.111	0.421	0.112	0.139
	(0.022)***	(0.026)***	(0.026)***	(0.023)***	(0.030)***	(0.030)***
Age of household head	−0.018	−0.015	−0.014	−0.010	−0.006	−0.006
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Head is married	−0.261	−0.257	−0.262	−0.244	−0.239	−0.228
	(0.017)***	(0.017)***	(0.016)***	(0.018)***	(0.019)***	(0.019)***
Female-headed household	−0.170	−0.108	−0.100	−0.191	−0.070	−0.051
	(0.018)***	(0.020)***	(0.019)***	(0.018)***	(0.020)***	(0.020)**
Elementary		0.071	0.090		0.107	0.106
		(0.017)***	(0.014)***		(0.017)***	(0.016)***
High school		0.227	0.263		0.319	0.333
		(0.020)***	(0.017)***		(0.022)***	(0.021)***
Beyond high school		0.554	0.598		0.718	0.737
		(0.025)***	(0.024)***		(0.031)***	(0.034)***
Constant	9.428	9.251	9.204	9.877	9.607	9.669
	(0.033)***	(0.037)***	(0.093)***	(0.040)***	(0.041)***	(0.057)***
Head's employment Industry	No	Yes	Yes	No	Yes	Yes
Head's employment status	No	No	Yes	No	No	Yes
Region fixed effect	No	No	Yes	No	No	Yes
Adj R^2	0.177	0.255	0.271	0.134	0.251	0.267
Σ	0.568	0.541	0.536	0.619	0.579	0.574
Number of observations	19,308	17,594	17,594	18,573	16,504	16,186

Notes: Robust standard errors clustered on Woreda ID level are given in parentheses.

*$p < .1$; **$p < .05$; ***$p < .01$.

APPENDIX B

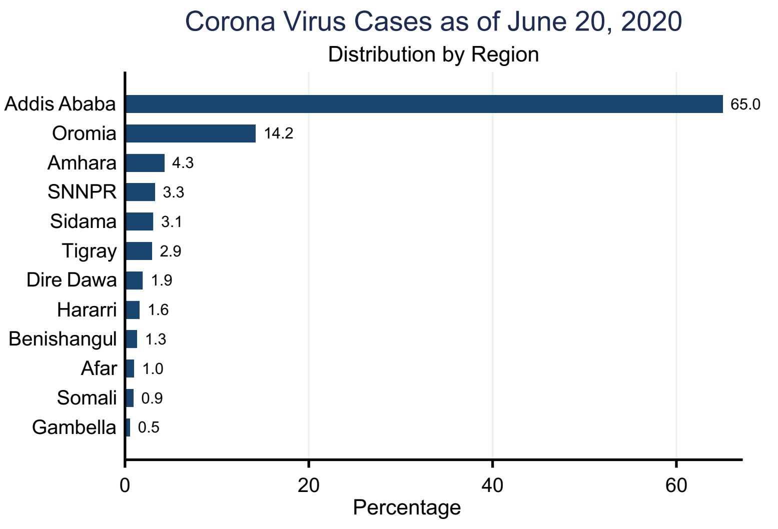

FIGURE A1 COVID-19 cases by region. *Source*: Own computation based on data from Ethiopian Public Health Institute [Colour figure can be viewed at wileyonlinelibrary.com]

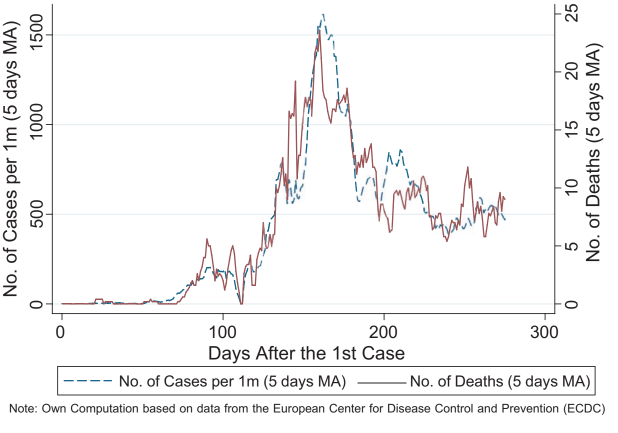

FIGURE A2 COVID-19 cases and deaths: five days moving average: December 14, 2020. Own computation based on data from the European Center for Disease Control and Prevention (ECDC) [Colour figure can be viewed at wileyonlinelibrary.com]

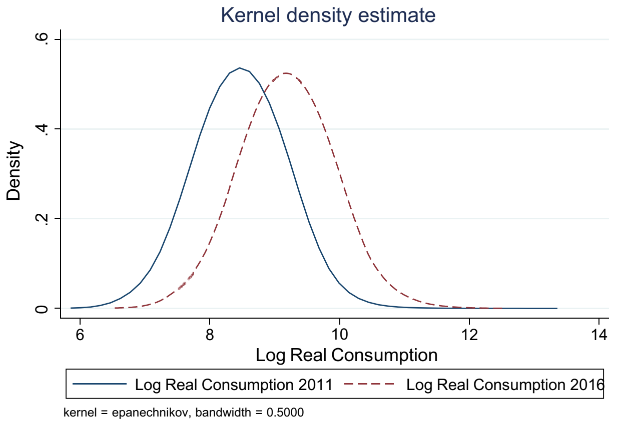

FIGURE A3 Distribution of log real consumption per adult equivalent: 2011 versus 2016 [Colour figure can be viewed at wileyonlinelibrary.com]

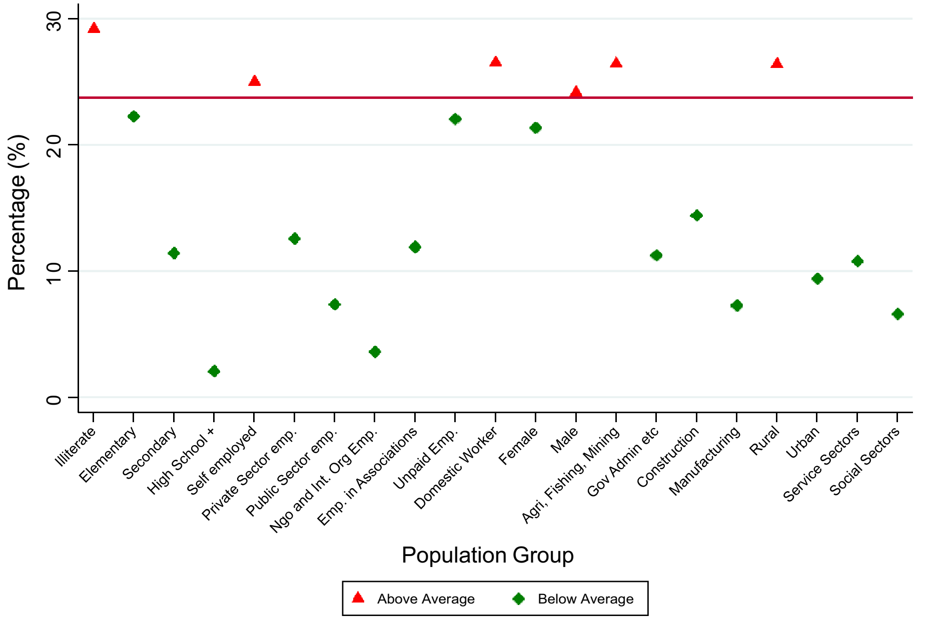

FIGURE A4 Chronic poverty and correlates of poverty: 2011 versus 2016 [Colour figure can be viewed at wileyonlinelibrary.com]

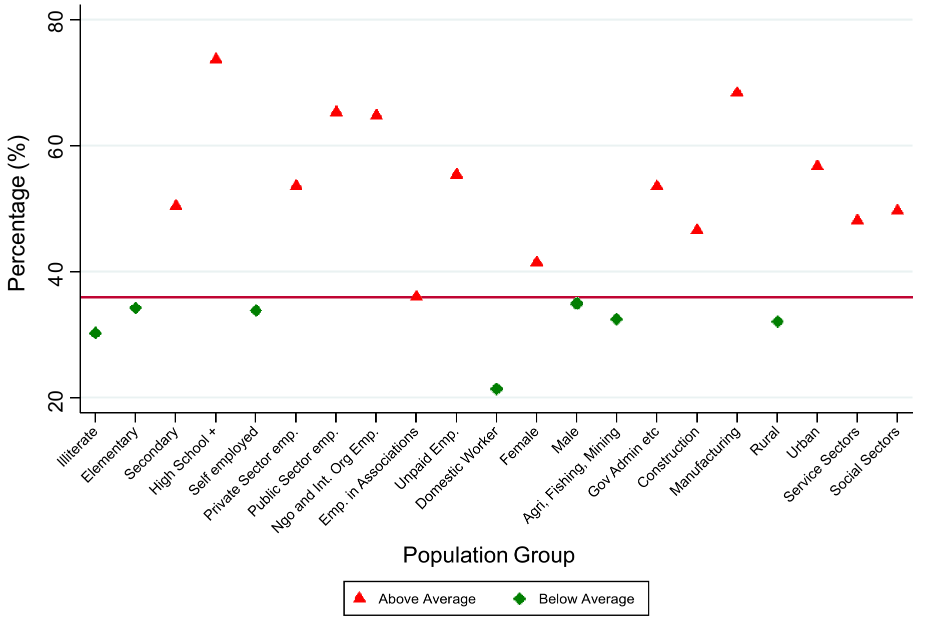

FIGURE A5 Upward poverty mobility and correlates of poverty: 2011 versus 2016 [Colour figure can be viewed at wileyonlinelibrary.com]