DEEP WORKING PAPER 07

Poverty and vulnerability transitions in Myanmar: An analysis using synthetic panels

Ines A. Ferreira,
Vincenzo Salvucci and
Finn Tarp
University of Copenhagen, Copenhagen, Denmark

October 2021

About DEEP

Our mission is to build evidence, insights, and solutions that help end extreme poverty globally.

We aim to contribute to new global and national data and evidence that governments, decision makers, citizens and researchers can use to improve people's lives and support the world's poorest people in their efforts to escape extreme poverty.

We are a consortium of the Universities of Cornell, Copenhagen, and Southampton led by Oxford Policy Management, in partnership with the World Bank's Development Data Group and funded by the UK Foreign, Commonwealth & Development Office.

How to cite: Ferreira, I.A., Salvucci, V. and Tarp, F. (2021) 'Poverty and vulnerability transitions in Myanmar: An analysis using synthetic panels', *DEEP Working Paper 07,* Data and Evidence to End Extreme Poverty Research Programme, Oxford.

Available at: https://doi.org/10.1111/rode.12836

Follow the programme here:

Abstract

While Myanmar has achieved distinct progress in economic growth and poverty reduction over the past decade, extreme natural events, economic, political and social crises, and the ongoing Covid-19 shock pose serious challenges. This study complements previous analyses of poverty and vulnerability by providing a dynamic perspective for the period 2015–2017. Given the lack of longitudinal household data, the analysis relies on the synthetic panels approach to further our understanding of transitions between different states – poverty, vulnerability, non-poverty – and the characteristics of the households associated with these transitions. Among the main results, we find that there was a relatively high probability for people who were poor in 2015 to exit poverty in 2017, and that the probability of remaining in a vulnerable situation was non-negligible. Moreover, the results point to important differences in the probability of transitioning between different states depending on household and location characteristics. While the Covid-19 shock has likely increased the proportion of households in the vulnerable and poor groups, these results highlight the need to focus on households with specific characteristics that make them more at risk of remaining in, or falling into, poverty than the rest of the population in a context of diminishing poverty rates and localised vulnerability pockets.

Acknowledgments: This study was prepared under the ExPov/Data and Evidence to End Extreme Poverty (DEEP) project, which is funded with UK aid from the UK government and managed by Oxford Policy Management. The authors would like to acknowledge the great support provided by Peter Lanjouw, Gerton Rongen and David Garcés-Urzainqui in the preparation of the technical work supporting the present analysis. We also acknowledge with sincere gratitude the excellent advice from Emilie Perge, helpful comments by Jehovaness Aikaeli and Stevan Lee, and research assistance by Frederikke Mikkelsen. The usual caveats apply.

Keywords: poverty; vulnerability; poverty dynamics; synthetic panels; Myanmar.

JEL classification codes: I32; C53.

Table of contents

Abstract i
1 Introduction 1
2 Context: Poverty in 2015 and 2017, and the impact of Covid-19 3
3 Data 7
4 Methodology 9
5 Results 12
5.1 Poverty and vulnerability dynamics at the national level 12
5.2 Profiling poverty and vulnerability dynamics 14
6 Discussion 17
7 Conclusion 19
References 22
Tables 26
Figures 28
Appendix 44

1 Introduction[1]

Myanmar has achieved sustained economic growth and broad macroeconomic stability during the past decade (Economist Intelligence Unit, 2020). Poverty rates decreased from 2004/05 onwards and non-monetary dimensions of well-being also improved (Central Statistics Office (CSO), United Nations Development Programme (UNDP) and World Bank, 2018; 2019b). Growth rates remained above 5% in the period 2011–2018, and while growth was relatively low in 2016 (5.8%), it increased again in 2017/18 and 2018/19. Subsequently, Myanmar's economy suffered a significant slowdown in 2020, with the surge of the Covid-19 crisis.[2] The World Bank's Economic Monitor estimates a growth rate of 1.7% in 2019/20, compared to a rate of 6.8% in 2018/19, and projects a growth rate of 2% in 2020/21 (World Bank, 2020a).

The current Covid-19 crisis poses serious challenges for the future.[3] It is expected to affect poverty rates, reversing the country's recent progress. According to the macro-micro simulation model developed by the World Bank (2020a),[4] poverty rates will increase in 2020/21 and, without a substantial policy response, will only return to their pre-crisis levels in 2021/22 or later. Moreover, the Covid-19 crisis seems to affect relatively more some categories of households that were not considered among the most disadvantaged in the latest poverty assessments (MPF and World Bank, 2017; CSO, UNDP and World Bank, 2018; 2019b). While it is important to study the actual or expected impact of the Covid-19 shock on households' livelihood and poverty, no household data have been made available after the Covid surge that allow for rigorous evaluations of the effect of the shock as compared to pre-crisis conditions.

In this study, we focus on poverty dynamics in the period 2015–2017. We analyse the transitions between states of poverty, vulnerability and non-vulnerability during a 'normal' or 'moderately high-growth' period, not affected by a major – but specific – nation-wide shock, such as the Covid-19 pandemic. We recognise that the Covid-19 shock may have influenced the profiles of poverty and vulnerability transitions obtained. Nevertheless, our premise is that analysing poverty dynamics during a time of general rising prosperity can offer useful insights into those who are likely to be hit especially hard by the economic consequences of the Covid-19 pandemic, given that the vulnerable and chronically poor in more prosperous times are likely to be particularly affected by shocks. This is relevant as well given that, at the moment, nothing indicates that those who were more at risk of being vulnerable or poor

[1] The authors do not consider in the present study the violent changes after 1 February 2021.
[2] According to the World Food Programme (2020), Myanmar has the third-highest number of Covid-19 infections and the third highest death rate among the Association of Southeast Asian Nations (ASEAN).
[3] At the time of finalising this study, preparations were underway to start vaccination in the country.
[4] The model combines macroeconomic forecasts with micro-level data on household welfare, livelihoods, and other characteristics from the 2017 Myanmar Living Conditions Survey (MLCS).

before the Covid-19 shock are now less at risk or in a better situation (see Diao and Mahrt, 2020).

Given that recent, large-scale, nationally representative, longitudinal household data are not available,[5] we implement the synthetic panels approach introduced by Dang *et al*. (2014a) and Dang and Lanjouw (2013; 2014) to derive the probabilities of a poverty or vulnerability transition at national level and for different household categories. We apply this methodology to the 2015 Myanmar Poverty and Living Conditions Survey (MPLCS) and to the 2017 Myanmar Living Conditions Survey (MLCS). As a result, this analysis of poverty and vulnerability transitions aims to supplement the information from existing poverty assessments based only on cross-sectional data. Specifically, we: i) provide point estimates for poverty and vulnerability transitions; ii) propose a possible choice of a vulnerability line, linked to the probabilities of transition; and iii) present a profile of the main transition trajectories, highlighting the household and location characteristics that are more associated with particular upward/downward transitions and with poverty immobility.

Moreover, we aim to integrate the main results from our analysis with the available reports and articles describing the effects of the Covid-19 shock on the health sector, the economy and particular household categories. Following World Bank (2020a), we suggest that many more households from the most affected areas and sectors have fallen into the vulnerable or into the poor group due to the Covid-19 shock. Hence, we believe our results are relevant for responding to the challenges that Myanmar will face once the immediate health-related shock is over. The likely world and regional economic crisis will affect the whole country, which will generate a need for support also for the 'standard' or more 'long-term' poor and vulnerable categories.

The study proceeds as follows: Section 2 presents context and stylised facts with respect to poverty, as reported in the 2015 and 2017 poverty assessments; Section 3 describes the data and Section 4 presents our methodology; the results are presented in Section 5, while Section 6 discusses them and Section 7 concludes.

[5] While some of the households surveyed in the 2005 Integrated Household Living Conditions Surveys (IHLCS) were surveyed again in the 2010 IHLCS, and while some analysis of poverty dynamics appear in Schmitt-Degenhardt (2013), the same report states that: '*As the survey can track only a part of the households surveyed in 2005 again in 2010, the available data do not allow in depth analysis*' (Schmitt-Degenhardt, 2013: 11).

2 Context: Poverty in 2015 and 2017, and the impact of Covid-19

This section first summarises the main insights regarding poverty in Myanmar, relying on the poverty assessments produced using the 2015 MPLCS and the 2017 MLCS (Ministry of Planning and Finance (MPF) and World Bank, 2017; CSO, UNDP and World Bank, 2018; 2019a; 2019b), which are extremely useful for establishing the profile of the poor in the country at these two points in time. The section then provides a broad overview of the situation at the end of 2020.

It is important to frame the above reports within the recent history of Myanmar, given that a number of key events in the years 2015–17 shaped the country's socioeconomic and political context, and its relations with the rest of the world. In 2015, the National League for Democracy won the parliamentary elections in Myanmar, obtaining over 80% of the available seats. These elections ended more than five decades of military rule and signalled a new era of economic recovery, democratic transition, and much desired ethno-religious reconciliation. This was an enormous achievement in terms of democratisation of the country, and the party's leader, Aung San Suu Kyi, was a key figure in the elections.

At the same time, 2015 was also a landmark year in the long-standing Rohingya crisis. A report by the United Nations High Commissioner for Refugees (UNHCR) estimated that since 2014, approximately 94,000 refugees and migrants have departed by sea from Bangladesh and Myanmar, including 31,000 departures in the first half of 2015, with many dying of starvation, dehydration, beatings by smuggling crews, or as a result of fights on board ships (UNHCR, 2015). This crisis led many to criticise the government and its leaders' policies towards minorities. Nevertheless, economic growth mostly continued, notwithstanding severe flooding in the second half of 2015, which affected 12 out of 14 states/regions and hundreds of thousands of people (CNN, 2015) and the slowing down of investment, which was in part related to the elections (World Bank, 2015, p. 12). In 2017, about 700,000 Rohingya fled to neighbouring Bangladesh (Barany, 2017; 2019), which led to worsening living conditions for the Rohingya,[6] as well as severely damaging Myanmar's international image (BBC, 2019; Marks, 2018) and potentially affecting its growth rate, which reached a low point in 2019 (Figure 1).

Nonetheless, the robust poverty reduction process continued at least until 2017.[7] While about half of the population was poor in 2005 (48.2%), this was reduced to close to a fourth

[6] We note that it was not possible to survey the Rohingya population in the conflict-affected areas in 2017.
[7] It is important to note that CSO, UNDP, and World Bank (2018; 2019a; 2019b) report that it was not possible to survey households in northern parts of Rakhine State (Maungdaw and Buthidaung townships) and the Wa Self-Administered Division, which could lead to an underestimation of the poverty rate. Limitations in coverage are fully documented in the MLCS17 Technical Report (CSO, UNDP and World Bank, 2019a).

of the population in 2017 (24.8%). Within this period, the poverty rate followed a steadily decreasing trend: it was estimated to be 42.4% in 2010 and 32.1% in 2015. The number of poor people also decreased, from 18.7 million in 2005 to 11.8 million in 2017, and non-monetary dimensions of well-being improved as well (CSO, UNDP and World Bank, 2018; 2019b). The official poverty rates and the gross domestic product (GDP) growth rates over the period 2005–19 are presented in Figure 1.

Starting with the 2015 poverty report (MPF and World Bank, 2017), it emerges that the demographic structure is different for poor and non-poor households. Poorer households have on average more household members and more dependents, are less integrated in the formal economy, are more likely to be working solely in agriculture, and are more likely to own fewer and lower value assets. Poorer households are less likely to have access to basic services, such as safe water or electricity, and, importantly, are less likely to own a valid identity card or to have legal titles for their dwellings. In addition, a non-negligible portion of the population (14%) is near poor – i.e. living between the poverty line and the poverty line augmented by 20% – and an even greater portion of the population (30%) is within 50% of the poverty line. This delineates a situation of widespread vulnerability, in which the common occurrence of natural calamities or other shocks can push many households into poverty (MPF and World Bank, 2017).

The 2017 poverty report (CSO, UNDP and World Bank, 2019b) puts more emphasis on the geographic dimension of poverty in Myanmar. It indicates that Chin State has the highest incidence of poverty (58%), followed by Rakhine State (42%), while, in absolute terms, the states/regions where the most poor live are Ayeyarwady Region (1.8 million), Shan State (1.5 million) and Sagaing Region (1.5 million). In general, poverty is found to be more prevalent in rural than in urban areas (30.2% versus 11.3%), and the number of poor people is 6.7 times higher in rural areas (10.2 million versus 1.5 million). The 2017 report confirms that poorer households, on average, comprise a higher number of children and dependents, and are more likely to have heads with little or no education. Moreover, households working in agriculture are more likely to be poor, especially if this is their only form of occupation. With respect to vulnerability, the report reaffirms that a large part of the population has consumption levels that are close to the poverty line, and is thus highly vulnerable to shocks.

The 2017 report also presents an analysis of poverty dynamics by comparing the proportion of the population that could be considered poor, non-poor insecure (i.e. vulnerable) and non-poor secure in 2005 and 2017. It highlights that not only did the poor decline as a percentage of the population, but also the non-poor insecure and non-poor secure groups both expanded, representing a general overall upward mobility. The percentage of non-poor secure relative to the population increased from only 24% in 2005 to 42.3% in 2017 (CSO, UNDP and World Bank, 2019b).

Regarding poverty dynamics, we move in this study a step further and estimate the proportion of households that were poor (non-poor) in both 2015 and 2017, or that were poor (non-poor) in 2015 and non-poor (poor) in 2017. Moreover, we compute the probabilities of being poor or non-poor in 2017 if an individual was either poor or non-poor in 2015. Similar to the 2017 poverty report, we introduce a concept of vulnerability and subdivide the population into three groups. However, instead of computing the vulnerability line using an arbitrary scaling up of the poverty line, we derive it directly from an application of the synthetic panel methodology and from a pre-specified risk of falling into poverty for vulnerable individuals (see Sections 4 and 5).

According to the World Bank (2020a), the Covid-19 pandemic has had a severe impact on household welfare. The proportion of households experiencing moderate to severe food insecurity increased from 12% in August 2020 to 25% in October 2020. The most affected households were those working in retail and personal services, as well as transportation, manufacturing, construction and tourism. The same report highlights that negative impacts on their operations were reported by 87% of firms, and that close to one-third of households' main workers could not secure any form of paid work in October 2020 (World Bank, 2020a). Households relying on informal jobs and on remittances have also suffered relatively more than others from this shock. The inability to repay debt is high, and the poor are the most likely to rely on informal lenders charging high interest rates. Another report by CSO, Ministry of Finance, Planning and Industry (MOPFI) and UNDP (2020) confirms that between 2019 and 2020, on average, households saw a 46.5% drop in their income. While the biggest drop has been felt by previously financially secure households, poor and vulnerable households have also been heavily impacted.

Moreover, not all regions have been affected in the same way, with urban areas being subject to more restrictions. As at 25 December 2020 (Ministry of Health and Sports, 2020), the three state/regions with the greatest number of confirmed cases were Yangon (67.7% of all confirmed cases), Mandalay (10.5%) and Bago (6%). According to CSO, MOPFI and UNDP (2020), the biggest reduction in household income has been in urban households and households in the regions.

Attempts have been made to estimate the impact of the Covid-19 shock using different simulation methods (see World Bank, 2020a; Diao and Mahrt, 2020; Diao *et al*., 2020). In particular, using microsimulation models and data from the 2015 MPLCS, Diao and Mahrt (2020) estimate that incomes fell for both rural and urban households, but mainly for those relying more on vulnerable non-farm income sources, which in turn could have led to significant increases in poverty. Additionally, they estimate that while a number of non-agricultural economic activities might recover relatively quickly to near normal levels of activity, between 350,000 and 650,000 households could nonetheless remain poor, depending on the speed of the recovery. Most households remaining in poverty are rural, including both farm and non-farm households. This study complements this type of analysis based on microsimulation techniques by focusing on the poverty dynamics (and underlying characteristics) during a period of economic prosperity and analysing the transitions between states of poverty and vulnerability.

3 Data

In this section we provide a brief description of the two datasets used in this study, the 2015 MPLCS (PMLCS15) and the 2017 MLCS (MLCS17) (MPF and World Bank, 2017; CSO, UNDP and World Bank, 2018; 2019a). While other surveys focusing on poverty exist, they are not representative at the national level.[8]

The MPLCS15 was conducted in early 2015 to analyse living conditions in Myanmar. It is representative at the national, urban/rural and agro-ecological zone level, and it is a relatively small-scale survey, with a sample size of 3,648 households. The survey includes different modules, including on basic household characteristics, housing and education. The MPLCS15 was implemented under the oversight of MPF, and supported by the World Bank Living Standards Measurement Studies and Poverty and Equity teams (MPF and World Bank, 2017).

The MLCS17 was conducted over a 12-month period from December 2016 to November 2017 and is more wide-ranging than the MPLCS15. While, similarly to the MPLCS15, the MLCS17 is representative at the national and urban/rural level, it is also representative of the states and regions of Myanmar. Moreover, each of the four survey quarters can be regarded as an independent nationally representative household survey.[9] The MLCS17 has a much larger sample size than the MPLCS15, with 13,730 households, and it includes several aspects of the country's living conditions, including household composition and demographics, and education and literacy. The survey was conducted by the CSO of Myanmar, with technical and financial support from the UNDP and the World Bank (CSO, UNDP and World Bank, 2018; 2019a; 2019b).

This description highlights that the MPLCS15 and the MLCS17 are not completely comparable databases. Although the master sample obtained from the 2014 Myanmar Census of Population and Housing was used as the basis for both the sample design of the MPLCS15 and for the selection of the enumeration areas of the MLCS17, the MLCS17 Technical Report lists the differences in the sample design implemented (CSO, UNDP and World Bank, 2019a).[10] In particular, the geographic domains of analysis for the MPLCS15

---

[8] For example, the Livelihoods and Food Security Trust Fund (LIFT) conducted a household survey in 2011, 2013 and 2015 in rural areas covered by LIFT programmes.

[9] Given this difference between the 2015 and the 2017 surveys, and to account for a possible role of seasonality in explaining the big change in poverty between them, we checked the seasonal poverty data. The 2017 poverty rate is largely comparable in all survey quarters (24.41% in quarter 1 (Q1), 23.88% in Q2, 24.18% in Q3 and 26.74% in Q4, with a yearly average of 24.8%), and in all seasons (23.96% percent in winter (Dec–Feb), 24.44% in the dry season (Mar–May), 25.25% in the rainy season (Jun–Oct), and 25.83% in the subsequent winter season (Nov–Dec)). Thus, the poverty rate gets slightly higher only towards the final months of 2017. Furthermore, if we compute the poverty rate using for 2017 only the households interviewed from January to April (which are the months in which the 2015 survey was conducted), we obtain a poverty rate of 23.9%, which is even lower than the official figure for 2017 (24.8%.

[10] As noted in Section 2, in 2017 it was not possible to survey two townships in Northern Rakhine that are home to an important Muslim and poor population, which could have affected the poverty rate. According to the

were not the states/regions, but five agro-ecological zones, obtained as a combination of states/regions. This entails that the estimates at the state/regional level for the MPLCS15 cannot be taken as completely reliable, given this difference in the sample design (CSO, UNDP and World Bank, 2018; 2019a). Nonetheless, simulations were conducted to make results comparable also at the state/region level,[11] and an effort was made to maintain comparability with past surveys throughout the preparation and development of the MLCS17 (CSO, UNDP and World Bank, 2018; 2019a).

MLCS17 Technical Report (CSO, UNDP and World Bank, 2019a), an adjustment of the sample weights to provide an accurate comparison between 2015 and 2017 produces a lower poverty rate (30.5%), which is only slightly lower than the official figure for 2015 (32.07%). While we do not perform this sample weights adjustment, when we exclude the two above-mentioned townships, we nevertheless obtain a poverty rate for 2015 which is only slightly lower (31.17%) than the official figure. This is likely due to the fact that only 72 observations would be dropped from the final sample if we excluded the two townships in Northern Rakhine, and they do not affect the poverty rate and poverty transitions in a substantial way.

[11] As an example, CSO, UNDP and World Bank (2019a: 59) report as follows: '*In reviewing the sampling errors and design effects for the estimates of average per capita expenditure from the 2015 MPLCS data, it was found that Yangon, Shan and Ayeyarwady have the higher design effects and variability, so it was decided to allocate a slightly larger sample for these domains*.'

4 Methodology

To study poverty dynamics using only cross-sectional survey data, we use the synthetic panels approach introduced by Dang *et al*. (2014a) and Dang and Lanjouw (2013; 2014), which makes it possible to construct synthetic panel data from repeated cross-sections. We refer to these authors for more details and a formal presentation of the approach, as well as to Garcés-Urzainqui *et al*. (2022). We provide here a brief summary. First, an imputation procedure is implemented so that the values of the relevant welfare aggregate (i.e. income or consumption) for households observed at time 2 are estimated using households and community characteristics and welfare aggregates measured at time 1 (Dang *et al*., 2014a; Dang and Lanjouw, 2013).

One of the assumptions in synthetic panels is that data are comparable. In particular, it is possible to use time-invariant household characteristics to predict household consumption at a previous point in time only if the underlying population is the same in all survey rounds. This implies, for example, that the sampling methodology is not modified over time. Thus, some discussion is needed for the surveys considered in this study, given the aforementioned changes that occurred from the MPLCS15 to the MLCS17 in terms of sampling methodology and representativeness of the sample, as well as the efforts made to make poverty and general welfare results comparable over time. While we recognise that the non-complete comparability of the underlying populations at these two points in time imposes some limitations, we believe that applying the synthetic panels to these surveys, but considering for the underlying consumption model only strictly time-invariant characteristics, is a realistic and sensible starting point in the analysis of poverty dynamics in Myanmar. The underlying population might also change due to alterations in the household composition (births, deaths, migration, etc.), but this can be overcome by restricting the sample. The second assumption is that the correlation between the error terms of the consumption model in the two survey rounds should be non-negative. Dang *et al*. (2014a) outline the reasons why this assumption is expected to be satisfied in most applications, and state that the two abovementioned assumptions are generally satisfied if the sample is restricted to households whose head is between 25 and 55 years old, as derived from the pseudo-panel literature (Dang *et al*., 2014a). Therefore, we make this restriction in the sample in the first survey round, and the age range is restricted accordingly in subsequent survey rounds.

After having estimated the welfare aggregate (income or consumption) that round 2 households would have had in round 1, it is then possible to estimate the degree of mobility in and out of poverty, and to compute, for example, what fraction of households in the population is poor (non-poor) in round 1 and non-poor (poor) in round 2. To estimate bounds for such quantities, we apply the non-parametric and the parametric approaches presented in Dang *et al*. (2014a: 113–115) and Dang and Lanjouw (2013), and discussed in further detail in Garcés-Urzainqui *et al.* (2022), to the analysis of poverty transitions using the two most recent available survey data. However, we mainly present the point estimates obtained using the parametric approach. The consumption model implemented here is relatively conservative: only those variables that are more strictly time invariant are included, such as gender, age and education level of the household head; however, we also add rural and region/state dummies to the analysis. These variables were selected based on existing literature on the application of synthetic panels in various settings,[12] as well as on data availability. Moreover, a series of variables concerning ownership of durable goods is considered as well, given that the information on when the good was purchased was available in the database, rendering it possible to know whether goods were already owned by the households at time 1 (i.e. 2015) (see Dang *et al*., 2014a).[13]

Following Dang and Lanjouw (2014), we also implement an analysis of vulnerability by identifying a group of vulnerable individuals within the non-poor group. This type of analysis allows us to define a vulnerability line from a pre-specified index of vulnerability and to create three groups: i) the poor (i.e. those individuals whose consumption lies below the poverty line); ii) the vulnerable (i.e. those whose consumption lies between the poverty line and the vulnerability line); and iii) the non-vulnerable (i.e. those individuals whose consumption lies above the vulnerability line). Dang and Lanjouw (2014) define the third group as 'middle-class', 'secure' or 'prosperous'. We use 'middle-class' in what follows.

Dang and Lanjouw (2014) recommend deriving the vulnerability line from a specified index of vulnerability instead of setting it at a value that would be an arbitrary scaling up of the poverty line. It is defined either as the probability of becoming poor at time 2 conditional on being in the middle class at time 1 — defined as the 'insecurity index', P^1— or as the probability of becoming poor at time 2 conditional on being vulnerable at time 1 — defined as the 'vulnerability index', P^2 (Dang and Lanjouw, 2014).[14] Once the value of the insecurity index, P^1, or the value of the vulnerability index, P^2, are selected, it is possible to derive the value for the vulnerability line.[15] In what follows, we consider the 'vulnerability index', P^2, to

---

[12] A summary is contained in Garcés-Urzainqui *et al*. (2022).

[13] Given the points made in the previous section on the potential effects of seasonality, and of the lack of coverage in two poor townships in Northern Rakhine in 2017, we checked the robustness of our results. First, we repeated the poverty transition analysis using for 2017 only the households interviewed from January to April 2017. The results are qualitatively and quantitatively very close to those included in our study. Second, we repeated the poverty transition analysis excluding from the 2015 survey the two townships in Northern Rakhine. The aggregate transition probabilities are not affected, and specific transition probabilities computed for Rakhine State and for the Muslim population are also not (or only marginally) affected.

[14] For the properties of these indexes, see Dang and Lanjouw (2014).

[15] The vulnerability index is supposed to be based on budgetary planning or social welfare objectives specific to the country under analysis: either because the country might be willing to accept only up to a certain risk of falling into poverty for vulnerable or middle-class individuals; or because the country might have only a limited budget available to address the vulnerability-to-poverty risk for the non-poor. In these cases, the flexibility of the approach outlined in Dang and Lanjouw (2014) might present some advantages in terms of transparency of criteria and policy design.

be equal to 15%.[16] From this value, we derive a vulnerability line equal to 2,035 kyats, which is equivalent to a scaling up of the poverty line by 28%.[17]

Overall, the information gathered from extensive validation work, developed over recent years in different countries and based on actual panel data, makes us confident that the application of the synthetic panels method in contexts in which longitudinal panel data are not available offers valuable insights for the analysis of poverty dynamics.[18] In this study, population weights and other survey design features specific to the household budget surveys considered are applied, and in all the models presented the reference welfare aggregate is the (log of) real household consumption per adult equivalent (CSO, UNDP and World Bank, 2018; 2019a; MPF and World Bank, 2017).

[16] This level of the vulnerability index, P^2, was used, among others, in Dang and Dabalen (2017), and was applied to a wide set of countries.
[17] This is close to the approach followed by Vietnam, where the vulnerability line is obtained as a scaling up of the poverty line by 30% (World Bank, 2012; Dang and Lanjouw, 2014). This vulnerability line is also close to the threshold considered in the MLCS17 for defining the non-poor secure (those with per adult equivalent daily expenditures higher than 1.5 times the poverty line, i.e. higher than 2,385 kyats) (CSO, UNDP and World Bank, 2019b).
[18] See Dang and Lanjouw (2015); Dang *et al*. (2014b); Bierbaum and Gassmann (2012); Bourguignon *et al*. (2015); Cruces *et al*. (2015); and Dang and Lanjouw (2018).

5 Results

In this section, we put forward the main results with respect to poverty dynamics over the period 2015–17. First, we present the consumption model and the upper and lower bounds for poverty and vulnerability mobility and immobility at national level estimated using the non-parametric approach, together with the poverty and vulnerability dynamics point estimates obtained using the parametric approach (Section 5.1). These estimates are subsequently further analysed and discussed in relation to selected household and geographic characteristics to present a profile of poverty and vulnerability mobility and immobility (Section 5.2).

5.1 Poverty and vulnerability dynamics at the national level

To analyse poverty dynamics in the period 2015–017 we implemented a consumption model regression including those covariates that we consider more likely to be time invariant: gender and age of the household head, marital status, ability to read and write, education level of the household head, type of ID card, religion,[19] mother tongue, state/region and dummies for urban/rural areas, plus variables on the possession of various assets in 2017 for which it was possible to recollect the information from 2015.[20] As discussed, the sample is restricted to households whose head is between 25 and 55 years old in the first survey round under analysis, and the age range is restricted accordingly in subsequent survey rounds.[21] Summary statistics for the variables included and for all survey rounds, obtained with the restrictions imposed on the age of the household head, are reported in Table A1 in the appendix. Results concerning the consumption model implemented for all available surveys are presented in the appendix, in Table A2. Based on the coefficients obtained from the consumption model, and using the non-parametric approach, we computed the conditional and unconditional probabilities shown in Table 1 in the columns 'bounds'. It is worth noting that the boundaries of the estimated poverty dynamics are not very wide, compared to other applications of this methodology.[22] The unconditional probabilities presented in Table 1, Panel a, give the fraction of population in the selected age range that is

---

[19] The largest (and poorest) Muslim population in Rakhine could not be surveyed.
[20] We consider ownership of battery/inverter/generator, stove/hotplate/rice cooker, electric iron, fan, refrigerator, washing machine, radio/stereo/TV, computer, landline/mobile phone/smartphone, bike, motorbike, motor vehicle.
[21] Also, households from northern parts of Rakhine State (Maungdaw and Buthidaung townships) and the Wa Self-Administered Division are excluded from the analysis, given that it was not possible to survey them in 2017 (CSO, UNDP and World Bank, 2019a).
[22] The width of the estimated boundaries depends on the quality of the underlying consumption model: namely, the overall explanatory power and the statistical significance of the individual regressors. Since we had relatively numerous time-invariant characteristics that could be reasonably included in the consumption model presented, this greatly increased the quality of the overall model and helped take into account shocks occurred at the urban/rural and state/region level (Dang *et al*., 2014a). All the models are estimated at the household level and make use of population weights and cluster settings; the dependent variable is the log of real household consumption per adult equivalent.

in each of the four listed categories. For example, 'Poor, poor' indicates the fraction of the population that was poor in year 1 and poor in year 2. The conditional probabilities displayed in Table 1, Panel b, represent the probability of each of the four states. For example, 'Poor to poor' indicates the probability of being poor in year 2, given that the individual was also poor in year 1. Both sets of information are important for studying poverty mobility and poverty immobility. Finally, the third column in Table 1 presents the point estimates for poverty dynamics for the period 2015–17 obtained using the parametric estimation approach described in the methodology section. To obtain these point estimates, the correlation coefficient between household consumption in the two survey rounds, ρ, was estimated to be 0.86 (using equation 5 in Dang and Lanjouw, 2013). This is in line with theory that expects a value of ρ bounded in the interval [0, 1], even though it appears to be somewhat higher than that estimated in other contexts (see details in Garcés-Urzainqui *et al*., 2022).

The point estimates suggest that there is a relatively high probability for people who were poor in 2015 to exit poverty in 2017: above 40% (state 'poor to non-poor' in Panel b). Conversely, for non-poor individuals in 2015 the chance of becoming poor in 2017 is rather low, about 6% (state 'non-poor to poor' in Panel b).[23] With respect to poverty immobility, only 20% of the population is found to be poor in both years (state 'poor, poor' in Panel a), whereas more than 60% of the population is estimated to be non-poor in 2015 and 2017 (state 'non-poor, non-poor' in Panel a), and the probability of remaining non-poor in 2017 if the individual was non-poor in 2015 is extremely high, 94% (state 'non-poor to non-poor' in Panel b).

We then followed the approach described in Dang and Lanjouw (2013; 2014) to obtain an analysis of vulnerability transitions, which adds important elements to the analysis of poverty just outlined. Within the non-poor group, we identify a group of vulnerable individuals, defined as those individuals whose consumption lies between the poverty line and the vulnerability line. Accordingly, we define the individuals whose consumption lies above the vulnerability line as 'middle-class'. Based on the poverty and vulnerability lines, we compute the conditional and unconditional transition probabilities for the three categories defined – poor, vulnerable and middle-class – applying synthetic panel techniques similar to those described above.[24]

These probabilities are represented in Table 2. We observe that only a tiny percentage of the population can be considered vulnerable in both periods (about 6%), and that for people in a vulnerable situation, it is relatively more likely that they will become non-vulnerable than that

[23] Not all the point estimates lie within the estimated bounds, but when this occurs the difference between the closest bound and the point estimate is very small. Also, the relatively high value of ρ, which is very close to 1 and thus implies a high correlation between household consumption in the two survey rounds, explains why many among the point estimates obtained are close to the upper bounds of poverty immobility (states 'poor, poor', 'non-poor, non-poor', 'poor to poor' and 'non-poor to non-poor' (see Table 1).
[24] Details are provided in Garcés-Urzainqui *et al*. (2022).

they will enter poverty (53% versus 15%), even though the probability of remaining in a vulnerable situation is also not negligible (about 32%) (Table 2, panel 'conditional probabilities', column 'point estimates'). Moreover, it is not unlikely for poor individuals in 2015 to become either vulnerable or middle-class in 2017 (probabilities of 27% and 16%, respectively), whereas downward transitions for the non-poor appear to be extremely unlikely, especially towards the poor group (less than 2% probability).

5.2 Profiling poverty and vulnerability dynamics

Our poverty and vulnerability dynamics estimates are analysed in relation to some of the household and geographic characteristics included in the consumption model, or other characteristics of interest, such as household head's employment, to present a tentative profile of poverty mobility and immobility, as outlined by, for example, Bierbaum and Gassmann (2012). This is particularly important in order to identify some of the correlates of the different transitions. We note that given that we just explore statistical associations, it is not possible in this context to analyse the underlying causes of different degrees of poverty mobility/immobility in particular regions or for specific household characteristics.

For each group of household and geographic characteristics, we focus on both poverty immobility and upward/downward transitions, considering both unconditional and conditional probabilities. The point estimates for both sets of probabilities obtained using the parametric approach are presented in Figures 2, 3 and 4.[25] In Figures 5, 6 and 7, we add the analysis of vulnerability to these results.[26]

5.2.1 Geographic differences

Regarding poverty immobility, we find that the probability for an individual to remain poor in 2017 if he/she was poor in 2015 ('poor to poor' in Figure 2) is about 43% for urban areas, and increases to 62% for rural areas. Moreover, the same probability is above 60% for individuals in the states/regions of Kachin, Kayah, Chin, Sagaing, Magway, Rakhine, Shan, Ayeyarwady and Naypyitaw.[27] The differences in the conditional probabilities of being vulnerable in 2017 given that the individual was also vulnerable in 2015 (Figure 5, Panel b) follow almost exactly the patterns, but differences between categories are less pronounced: households in rural areas, in the states/region of Kachin, Kayah, Chin, Sagaing, Magway,

---

[25] We do not discuss here the unconditional probabilities of the state 'non-poor, non-poor' because most of the time they provide a reverse profile of the state 'poor, poor', and the same applies to the conditional probabilities of the state 'non-poor to non-poor'.

[26] The states 'middle-class, middle-class' and 'middle-class to middle-class' are not discussed here as they are the almost exact mirror image of the results for the states 'poor, poor' and 'poor to poor'.

[27] 60% is taken as a reference here in that it roughly corresponds to the 'poor to poor' conditional probability at national level. Moreover, we note that given that poverty transitions are being computed using the characteristics in the MCLS 2017, which is representative at the state/region level, the distribution of characteristics used for prediction should also be representative, and the predictions for 2015 based on these characteristics are valid for the regions.

Rakhine, Shan, Ayeyarwady and Naypyitaw, present higher probabilities than the country average; this is also the case for households headed by someone without education or working in agriculture or mining.

With respect to downward transitions (Figure 3), both unconditional and conditional probabilities are very low and lie in the range 0–12%, while only minor differences are observed among different household categories. The biggest differences are found with respect to the probability of entering poverty in 2017 if the individual was non-poor in 2015 for households in Kachin, Magway, Rakhine and Ayeyarwady versus households in most other states/regions (9–12% versus about 5%). The states/regions with a lower probability of exiting poverty (Figure 4) are Kachin, Chin, Sagaing, Magway, Rakhine and Ayeyarwady, with conditional probabilities around 30%; while this probability is above 50% for households in Tanintharyi, Bago, Mandalay, Mon and Yangon. The difference of about 20 percentage points between urban and rural areas is also striking.

Moreover, the conditional probability of becoming poor in 2017 given that the individual was vulnerable in 2015 (Figure 6, Panel b) reaches about 30% for the states/regions of Kachin, Magway and Ayeyarwady. While the conditional probabilities for the state 'poor to vulnerable' (Figure 7, Panel b) are around 30% for most states/regions (the lowest values are found for the states/regions of Kachin, Chin, Magway, Rakhine and Ayeyarwady), we find somewhat bigger differences with respect to the state 'vulnerable to middle-class'. In this case, the highest upward conditional probabilities are associated with living in the states/regions of Chin, Tanintharyi, Bago, Mandalay, Mon and Yangon (between 60% and 80%) and with living in urban areas (64%).[28]

5.2.2 Characteristics of the household head

The probability for an individual remaining poor in 2017 if he/she was poor in 2015 ('poor to poor' in Figure 2) lies in the range 63–65% for households whose head works in agriculture, forestry and fishing or in mining and quarrying, and it is above 70% for households whose head has no education. It is 64% for people without a valid identity card and 60% for people whose mother tongue is not Burmese; also, it is close to 70% for Christians and other religions (Hindu, Animists, other or no religion). Moreover, households headed by someone without education or working in agriculture or mining show higher probabilities of remaining vulnerable in 2017 if they were vulnerable in 2015 than the country average (Figure 5, Panel b).

There are differences in the probability of entering poverty in 2017 (Figure 3) for households headed by someone with no education versus households headed by someone with tertiary education (about 11% and 2%, respectively). Still, more marked differences emerge when

[28] Clearly, the Covid-19 shock might have pushed the upward transition probabilities ('poor to vulnerable', 'poor to middle-class' and 'vulnerable to middle-class') towards the lower bounds.

analysing the unconditional probabilities of exiting poverty (Figure 4). It is much more likely for households headed by someone with some education to escape poverty: the difference between incomplete primary school and both complete primary school and incomplete secondary school is about 13 percentage points, but this difference increases to 30 percentage points for complete secondary school and tertiary education. The probability of escaping poverty in 2017 if the individual was poor in 2015 is lower for Christians and other religions (about 30%), and lower for those working in agriculture, forestry, fishing or mining and quarrying (about 35%).

When we consider vulnerability, the only conditional probabilities shown in Figure 6 (Panel b) that present values above the 0–15% range are those referring to the state ‘vulnerable to poor’. We estimate that the probability of becoming poor in 2017 given that the individual was vulnerable in 2015 is above 30% for households whose head is divorced, around 25% for households with heads with incomplete primary education, and above 20% for Christians and for other religions. Upward transitions (Figure 7) seem to be more likely than downward transitions for the majority of the categories considered. In particular, the conditional probabilities for the state ‘poor to vulnerable’ are around 30% for most of the categories relating to the characteristics of the household head.

5.2.3 Possession of durable goods

The probability for an individual remaining poor in 2017 if he/she was poor in 2015 (‘poor to poor’ in Figure 2) lies below 40% for households that own some less common durable goods, such as a refrigerator, washing machine, computer or motor vehicle. Furthermore, the possession of some durable goods is also linked with upward mobility. Differences in the probability of escaping poverty in 2017 if the individual was poor in 2015 (Figure 4) are found for households owning an electric iron, fan, refrigerator, washing machine, computer or motor vehicle compared to those that do not. Some of the highest upward conditional probabilities, ‘vulnerable to middle-class’ (Figure 7, Panel b), are associated with owning the most common durable goods, especially a motor vehicle (86%).

6 Discussion

This analysis highlights that significant differences exist in the probabilities of transition between states of poverty/vulnerability depending particularly on the state/region or area of residence and on the level of education of the household head, alongside other characteristics. We stress that the probability that an individual will remain poor in 2017 if he/she was poor in 2015 reaches 62% for rural areas. Moreover, the same probability is lower for the states/regions of Yangon, Mon, Mandalay, Tanintharyi and Bago than for most other states – the differences registered with respect to Kachin, Kayah, Chin, Sagaing, Magway, Rakhine and Ayeyarwady in some case exceed 30 percentage points.[29] The importance of education stands out as well, along with other factors that are also linked to poverty immobility, such as not having a valid identity card, working in agriculture or mining, and not owning some of the most common durable goods. Moreover, it is much more likely for households headed by someone with some education to escape poverty and become non-poor, and the difference is also striking between urban and rural areas.

When considering vulnerability, we estimate that falling into poverty given that the individual was vulnerable is more likely (around 25%) for households with heads with incomplete primary education and it reaches about 30% for the states/regions of Kachin, Magway and Ayeyarwady. Conversely, we estimate that upward transitions seem to be more likely than downward transitions for the majority of the categories considered. The probabilities of becoming vulnerable in 2017 if the individual was poor in 2015 are around 30% for most household and location categories, with the lowest values found for the states/regions of Kachin, Chin, Magway, Rakhine and Ayeyarwady. In this case as well, the highest probabilities of becoming middle-class if the individual was vulnerable are associated with living in the states/regions of Chin, Tanintharyi, Bago, Mandalay, Mon and Yangon, with living in urban areas, and with owning the most common durable goods, especially a motor vehicle.

Some of the household categories identified in existing reports as being heavily affected by the Covid-19 crisis do not appear in the poverty transitions presented here. For some of the

[29] As mentioned, the poverty transitions presented here do not allow for an analysis of the underlying causes of why we observe a high degree of poverty mobility/immobility in a particular region or for specific household characteristics. Nonetheless, previous poverty reports provide additional insights into the characteristics that might be associated with the fact that individuals in particular states/regions present higher than country average probabilities of remaining poor or of falling into poverty (together with a lower than average probability of exiting poverty if poor). First, these states/regions are also among the poorest areas in the 2017 poverty assessment, which can be associated with the fact that they have, on average, higher food expenditures as a share of total expenditures, among other factors (CSO, UNDP and World Bank, 2018; 2019a). Moreover, most states in the Hills and Mountains zone are above the national poverty headcount and have particularly high poverty depth, which points to the challenges connected with remoteness and the mountainous terrain (CSO, UNDP and World Bank, 2018; 2019a). Finally, for some states like Tanintharyi, despite the relatively high GDP per capita, access to basic and/or public services is not optimal: it was the only state/region that was not connected to the national electricity grid in 2017, and it suffers from relatively low educational outcomes.

most affected categories – urban households, children being forced out of schools, individuals working in the informal sector, in the tourism sector, in retail, transportation, in services in general, and in manufacturing, among others – the probabilities of falling into poverty given that the individual was non-poor might have easily increased towards the upper bound of the estimated interval.[30] Moreover, we are not able to take into account specific government interventions that might have mitigated the impact of the Covid-19 shock, for specific groups or for the whole population. Examples of this include the increased number of households that were entitled to receive cash transfers during 2020, or the provision of free electricity to a wide range of households and companies (World Bank, 2020a). Given the nature of the synthetic panels analysis, it is not even possible to take into account significant population movements from one region/state to the other. There is evidence that during the Covid-19 shock a non-negligible number of migrant workers, based for example in the productive regions of Yangon and Bago, returned to their hometowns (International Labour Organization, 2020). If properly accounted for, this would of course affect poverty dynamics. The results of these unaccounted dynamics, which are specific to 2020, will become evident once household data collected after the Covid-19 shock become available.

Nonetheless, we believe that our analysis still offers a fairly robust profile of poverty dynamics in 'normal' times, and it provides useful insights into those household characteristics that may be particularly associated with, for example, poverty immobility or downward transitions from vulnerability to poverty as a consequence of different shocks. Thus, the fears of the consequences of the shock induced by the Covid-19 pandemic are even greater when one considers the high levels of persistence of poverty in some areas of the country and for some household categories. This is more so given that the average probability of upward mobility in most of these areas and for most of these categories was already much lower than the national average, even in a period of high growth. This raises concerns that these upward transition probabilities might have lowered even more with the ongoing situation. Also, in light of the Diao and Mahrt (2020) estimates of the number of households remaining in poverty after the crisis, it seems unlikely that those households that were already more at risk of being poor, or that were less likely to become non-poor in high-growth times, would be better off during the Covid-19 crisis.

[30] As seen in Table 1, Panel b, the estimated intervals can be rather wide. At national level, the point estimate for the conditional probability 'non-poor to poor' is 0.056, but the upper bound is as high as 0.231.

7 Conclusion

In this study we have provided insights into poverty and vulnerability dynamics in Myanmar using the two most recent available survey data, the MPLCS15 and the MLCS17. After years of sustained growth, macroeconomic stability, increased political stability and robust poverty reduction, Myanmar has experienced economic slowdown due to several factors. The Covid-19 shock in 2020 posed new challenges and further highlighted the need to understand the transitions to and from poverty and vulnerability. While longitudinal datasets are not available, using the synthetic panels approach enabled us to analyse poverty and vulnerability dynamics in a key period, 2015–17, and to identify characteristics associated with transitions between different states.

At national level, we estimated that for people who were poor in 2015 there was a probability of about 40% of exiting poverty in 2017, while for non-poor individuals in 2015 the chance of becoming poor in 2017 was only about 6%. While recognising that this might have changed during the Covid-19 shock, we also find that people in a vulnerable situation are relatively more likely to become non-vulnerable than to enter poverty (50% versus 15%), but at the same time the probability of remaining in a vulnerable situation is non-negligible at national level (about 35%).

It emerges from the analysis that there are a number of household characteristics for which: i) the probability of being poor in both periods is relatively high; ii) the probability of falling into poverty if the individual was already poor is higher than the country average; and, consistently, iii) the probability of exiting poverty in 2017 if the individual was poor in 2015 is lower than the country average. In particular, these characteristics include households in rural areas; and in the states/regions of Kachin, Kayah, Chin, Sagaing, Magway, Rakhine, Shan, Ayeyarwady and Naypyitaw. The same goes for households with heads working in agriculture or mining; households headed by someone with no education, without a valid identity card, whose mother tongue is not Burmese, professing religions other than Buddhism and Islam,[31] and not owning some common durable goods. This is in contrast with households in urban areas; in the states/region of Tanintharyi, Bago, Mandalay, Mon and Yangon; headed by someone with completed secondary school, with a valid identity card and working outside agriculture and mining; and households owning more common durable goods. They appear as being relatively less prone to falling into poverty than the rest of the population. This may have changed with the Covid-19 shock, which might have put a halt to this positive, though not evenly distributed, situation of increasingly low levels of poverty and relatively low persistence of poverty for the latter categories.

[31] We highlight that the largest (and poorest) Muslim population in Rakhine could not be surveyed, so the results with respect to the Muslim population are to be interpreted with caution.

As explained, an important limitation of this study is that we mostly describe a profile of poverty dynamics in 'normal' times of moderately high growth and poverty reduction, and do not directly take the Covid-19 shock into account. This shock struck at a time when growth rates were high but already experiencing a contraction, so it is reasonable to expect that the poverty/vulnerability patterns outlined using 2015–17 data worsened during 2020. Still, our conjecture is that the analysis of poverty dynamics during a period of general prosperity provides a useful window on those who may be particularly affected by the economic consequences of the Covid-19 pandemic.

The proportion of households in the vulnerable and poor group has certainly increased as a consequence of the shock, likely including household categories that were previously regarded as less vulnerable, as also indicated in previous work and recent reports (CSO, MOPFI and UNDP, 2020). Covid-19 related restrictions are increasing the risk of entering poverty for more households, especially for those described as being hit hardest by the shock (World Bank, 2020a) and many rural households may also have fallen into poverty from a situation of vulnerability and are unlikely to recover in the short run (Diao and Mahrt, 2020). For the most affected categories, the probabilities of falling into poverty given that the individual was non-poor might have easily increased towards the upper bound of the estimated intervals. At the same time, our results showing high levels of persistence of poverty and the low levels of upward mobility in some areas of the country and for some household categories make the consequences of a shock like the pandemic even more worrying, raising concerns that the probability of upward transition might have lowered even more. Furthermore, while 'new' vulnerable groups may have emerged, it seems unlikely that households and individuals who were already poor or vulnerable in high-growth times would be better off during the crisis, and the 'standard' or 'long-term' poverty and vulnerability drivers have not disappeared.

As discussed, a further limitation relates to the limits of the synthetic panel method. If only a limited number of time-invariant variables are available, the method provides less precise estimates for poverty and vulnerability transitions. We can in part overcome this limitation using a parametric approach, as outlined in the methodology section, yet this requires additional assumptions about the error distribution.

At any rate, we believe the results in this study to be relevant, especially as and when more 'normal' poverty and vulnerability dynamics are reinstated. This is so given that in a situation of diminishing poverty rates and localised vulnerability pockets these results highlight the need to focus on households with the specific characteristics outlined above, which make them more at risk of remaining poor or falling into poverty compared to the rest of the population. In sum, the dynamic perspective offered by these results highlights the need for a renewed commitment to rethinking existing social protection programmes and designing new ones. This is so especially for region- and sector-specific inclusive poverty/vulnerability programmes, and particular attention should be given to both poverty at a specific point in time as well as its dynamics, and to the transition between different poverty/vulnerability states.

References

Barany, Z. (2017) 'Myanmar's Rocky Road to Democracy', Istituto Affari Internazionali, http://www.jstor.org/stable/resrep09789.

Barany, Z. (2019) 'The Rohingya Predicament. Why Myanmar's Army Gets Away with Ethnic Cleansing', Istituto Affari Internazionali, https://www.jstor.org/stable/resrep19683?seq=1#metadata_info_tab_contents.

BBC (2019) 'Rohingya crisis: US imposes sanctions on top Myanmar generals', *BBC*, 17 July 2019, https://www.bbc.com/news/world-asia-49014631.

Bierbaum, M. and Gassmann, F. (2012) 'Chronic and Transitory Poverty in the Kyrgyz Republic: What Can Synthetic Panels Tell Us?', *MERIT Working Paper 064*, United Nations University–Maastricht Economic and Social Research Institute on Innovation and Technology, Maastricht.

Bourguignon, F., Moreno, H. and Dang, H.-A. (2015) 'On the Construction of Synthetic Panels', presented at the North East Universities Development Consortium annual conference, Brown University, Providence RI.

CNN (2015) 'Flooding in Asia displaces millions; death toll rising rapidly', *CNN*, 6 August 2015, https://edition.cnn.com/2015/08/05/asia/flooding-asia-displaces-millions/. [Accessed 16 July 2021].

Cruces, G., Lanjouw, P., Lucchetti, L., Perova, E., Vakis, R. and Viollaz, M. (2015) 'Estimating Poverty Transitions Repeated Cross-Sections: A Three-Country Validation Exercise', *Journal of Economic Inequality* 13, pp. 161–179, https://doi.org/10.1007/s10888-014-9284-9

CSO, MOPFI and UNDP (2020) 'Household Vulnerability Survey (HVS) Key Findings: Rapid assessment of the economic impact of COVID-19 restrictions on vulnerable households', CSO, MOPFI and UNDP, Nay Pyi Taw and Yangon, https://www.csostat.gov.mm/AvailableBookshop/Availablenow

CSO, UNDP and World Bank (2018) 'Myanmar Living Conditions Survey 2017: Key Indicators Report', Ministry of Planning and Finance, UNDP and World Bank, Nay Pyi Taw and Yangon, http://documents1.worldbank.org/curated/en/739461530021973802/pdf/Myanmar-Living-Conditions-Survey-2017-Key-Indicators-Report.pdf

CSO, UNDP and World Bank (2019a) 'Myanmar Living Conditions Survey 2017: Technical Report', Ministry of Planning and Finance, UNDP and World Bank, Nay Pyi Taw and Yangon, https://www.csostat.gov.mm/FileUpload/cso/LatestInformation/MLCS_Technical_Report.pdf

CSO, UNDP and World Bank (2019b) 'Myanmar Living Conditions Survey 2017: Poverty Report', Ministry of Planning and Finance, UNDP and World Bank, Nay Pyi Taw and Yangon, http://documents1.worldbank.org/curated/en/921021561058201854/pdf/Myanmar-Living-Condition-Survey-2017-Report-3-Poverty-Report.pdf

Dang, H.-A. and Dabalen, A. L. (2017) 'Is Poverty in Africa Mostly Chronic or Transient? Evidence from Synthetic Panel Data', *Policy Research Working Paper 8033*, World Bank, Washington DC.

Dang, H.-A. and Lanjouw, P. (2013) 'Measuring Poverty Dynamics with Synthetic Panels Based on Cross-Sections', *World Bank Policy Research Working Paper # 6504*, World Bank, Washington, DC.

Dang, H.-A. and Lanjouw, P. (2014) 'Welfare Dynamics Measurement: Two Definitions of a Vulnerability Line and their Empirical Application', *Review of Income and Wealth* 63, pp. 633–660.

Dang, H.-A. and Lanjouw, P. (2015) 'Poverty Dynamics in India between 2004 and 2012: Insights from Longitudinal Analysis Using Synthetic Panel Data', *Policy Research Working Paper No. 7270*, World Bank, Washington, DC.

Dang, H.-A. and Lanjouw, P. (2018) 'Poverty Dynamics in India between 2004 and 2012: Insights from Longitudinal Analysis Using Synthetic Panel Data', *Economic Development and Cultural Change* 67, pp. 131–170, https://doi.org/10.1086/697555

Dang, H.-A., Lanjouw, P., Luoto, J. and McKenzie, D. (2014a) 'Using Repeated Cross-Sections to Explore Movements in and out of Poverty', *Journal of Development Economics* 107, pp. 112–128, https://doi.org/10.1016/j.jdeveco.2013.10.008

Dang, H.-A., Lanjouw, P. and Swinkels, R. (2014b) 'Who Remained in Poverty, Who Moved Up, and Who Fell Down? An Investigation of Poverty Dynamics in Senegal in the Late 2000s', *Policy Research Working Paper No. 7141*, World Bank, Washington DC.

Diao, X., Aung, N., Lwin, W. Y., Zone, P. P., Nyunt, K. M. and Thurlow, J. (2020) 'Assessing the Impacts of COVID-19 on Myanmar's Economy: A Social Accounting Matrix (SAM) Multiplier Approach', *Myanmar Strategy Support Program Working Paper 01 and Policy Note 05*, International Food Policy Research Institute, Yangon.

Diao, X. and Mahrt, K. (2020) 'Assessing the impacts of COVID-19 on household incomes and poverty in Myanmar: A microsimulation approach', *Myanmar SSP Working Paper 2*, International Food Policy Research Institute, Washington DC.

Economist Intelligence Unit (2020) 'Country Report: Myanmar', The Economist Intelligence Unit, London, UK.

Garcés-Urzainqui, D., Lanjouw, P. and Rongen, G. (2022) 'Constructing Synthetic Panels for the Purpose of Studying Poverty Dynamics: A Primer', *Review of Development Economics* (forthcoming).

International Labour Organization (2020) 'COVID-19: Impact on Migrant Workers and Country Response in Myanmar', ILO, Geneva, https://www.ilo.org/yangon/publications/WCMS_749466/lang--en/index.htm.

Marks, S. (2018) 'EU weighs new sanctions against Myanmar over Rohingya', *Politico*, 8 September 2018, https://www.politico.eu/article/eu-weighs-new-sanctions-against-myanmar-over-rohingya/.

Ministry of Health and Sports (2020) 'Situation report – 262', Ministry of Health and Sports, Department of Public Health, Central Epidemiology Unit, Nay Pyi Taw, http://mohs.gov.mm/su/orhx6034OR

MPF and World Bank (2017) 'An analysis of poverty in Myanmar. Poverty Profile', MPF and World Bank, Nay Pyi Taw and Yangon, http://documents1.worldbank.org/curated/en/829581512375610375/pdf/121822-REVISED-PovertyReportPartEng.pdf

Schmitt-Degenhardt, S. (2013) 'A regional perspective on poverty in Myanmar', UNDP, file:///H:/Poverty/Myanmar/A%20regional%20perspective%20on%20poverty%20in%20Myanmar.pdf

UNHCR (2015) 'South-East Asia mixed maritime movements April – June 2015', UNHCR Regional Office for South-East Asia, https://www.unhcr.org/53f1c5fc9.html

World Bank (2012) '2012 Vietnam Poverty Assessment Report: Well Begun, Not Yet Done – Vietnam's Remarkable Progress on Poverty Reduction and the Emerging Challenges', World Bank, Hanoi, https://documents.worldbank.org/pt/publication/documents-reports/documentdetail/563561468329654096/2012-vietnam-poverty-assessment-well-begun-not-yet-done-vietnams-remarkable-progress-on-poverty-reduction-and-the-emerging-challenges

World Bank (2015) 'Myanmar Economic Monitor: Staying the Course on Economic Reforms', World Bank, Washington DC, https://documents1.worldbank.org/curated/en/193541467998792817/pdf/99930-REVISED-PUBLIC-MEM-October-2015.pdf

World Bank (2020a) 'Myanmar Economic Monitor Dec 2020: Coping with COVID-19', World Bank, Washington DC, http://documents1.worldbank.org/curated/en/906171608086222905/pdf/Myanmar-Economic-Monitor-Coping-with-COVID-19.pdf

World Bank (2020b) 'GDP growth (annual %) – Myanmar. World Bank national accounts data, and OECD National Accounts data files', World Bank, https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?end=2019&locations=MM&start=2005.

World Food Programme (2020) 'WFP Myanmar: COVID-19 Situation Report #12.', World Food Programme, https://reliefweb.int/report/myanmar/wfp-myanmar-covid-19-situation-report-12-16-november-2020

Tables

Table 1: Poverty dynamics 2015–17, non-parametric estimates and point estimates of unconditional and conditional transition probabilities

Panel a	Bounds		Point estimates	Std. err.	[95% conf. interval]	
Poor, poor	0.202	0.077	0.203	0.003	0.198	0.208
Poor, non-poor	0.108	0.163	0.137	0.002	0.134	0.141
Non-poor, poor	0.051	0.176	0.035	0.001	0.034	0.036
Non-poor, non-poor	0.639	0.585	0.624	0.004	0.617	0.632
N	8,810	8,810	8,810			
Panel b	**Bounds**		**Point estimates**	**Std. err.**	**[95% conf. interval]**	
Poor to poor	0.650	0.322	0.567	0.003	0.562	0.573
Poor to non-poor	0.350	0.678	0.433	0.003	0.427	0.438
Non-poor to poor	0.074	0.231	0.056	0.001	0.054	0.058
Non-poor to non-poor	0.926	0.769	0.944	0.001	0.942	0.946
N	8,810	8,810	8,810			

Notes: Authors' calculations. Transition probabilities estimated using the national poverty lines in 2015 and 2017. Rows in Panel a give the fraction of population in the selected age range that is in each of the four categories. For example, 'Poor, poor' indicates the fraction that was poor in year 1 and poor in year 2. Bounds and point estimates are provided. Rows in Panel b give the probability of each of the four states. For example, 'Poor to poor' indicates the probability of being poor in year 2, given that the individual was also poor in year 1. Bounds and point estimates are provided in this case as well.

Table 2: Unconditional and conditional point estimates of poverty and vulnerability transitions probabilities, 2015–17 (vulnerability index, P^2 = 15%; vulnerability line = poverty line scaled up by 28%).

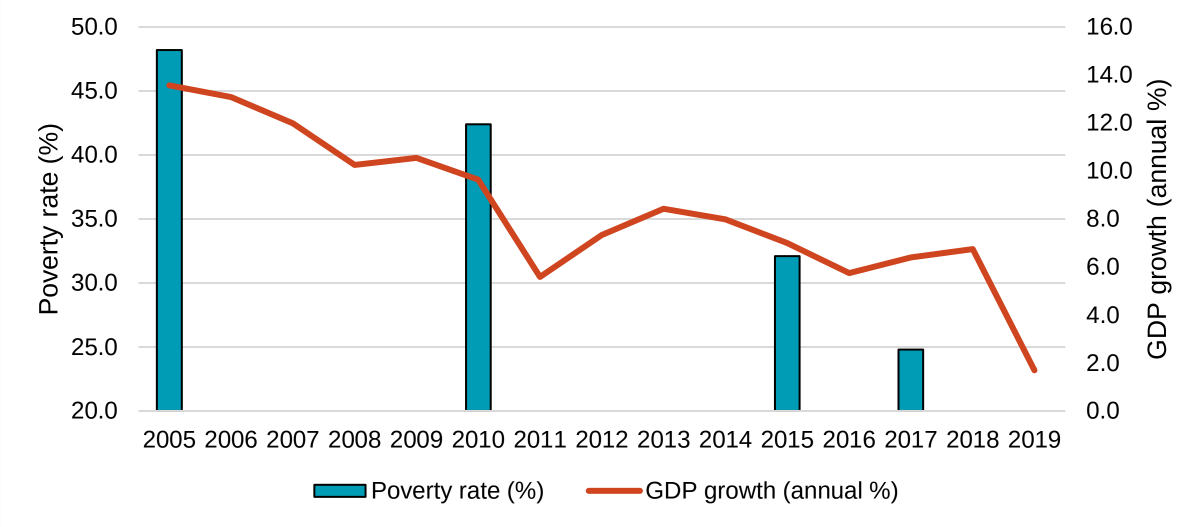
Unconditional probabilities	Point estimates	Std. err.	[95% conf. interval]	
Poor, poor	0.203	0.003	0.198	0.208
Poor, vulnerable	0.089	0.001	0.086	0.091
Poor, middle-class	0.049	0.001	0.047	0.051
Vulnerable, poor	0.027	0.000	0.026	0.028
Vulnerable, vulnerable	0.058	0.000	0.057	0.058
Vulnerable, middle-class	0.093	0.001	0.091	0.094
Middle-class, poor	0.008	0.000	0.007	0.008
Middle-class, vulnerable	0.040	0.001	0.038	0.041
Middle-class, middle-class	0.435	0.004	0.426	0.443
N	8,810			
Conditional probabilities	**Point estimates**	**Std. err.**	**[95% conf. interval]**	
Poor to poor	0.567	0.003	0.562	0.573
Poor to vulnerable	0.271	0.001	0.269	0.273
Poor to middle-class	0.162	0.002	0.158	0.166
Vulnerable to poor	0.150	0.002	0.146	0.155

Unconditional probabilities	Point estimates	Std. err.	[95% conf. interval]	
Vulnerable to vulnerable	0.318	0.002	0.315	0.321
Vulnerable to middle-class	0.532	0.003	0.525	0.539
Middle-class to poor	0.017	0.000	0.016	0.018
Middle-class to vulnerable	0.089	0.001	0.087	0.091
Middle-class to middle-class	0.894	0.002	0.891	0.897
N	8,810			
Unconditional probabilities	**Point estimates**	**Std. err.**	**[95% conf. interval]**	
Poor, poor	0.203	0.003	0.198	0.208
Poor, vulnerable	0.089	0.001	0.086	0.091
Poor, middle-class	0.049	0.001	0.047	0.051
Vulnerable, poor	0.027	0.000	0.026	0.028
Vulnerable, vulnerable	0.058	0.000	0.057	0.058
Vulnerable, middle-class	0.093	0.001	0.091	0.094
Middle-class, poor	0.008	0.000	0.007	0.008
Middle-class, vulnerable	0.040	0.001	0.038	0.041
Middle-class, middle-class	0.435	0.004	0.426	0.443
N	8,810			
Conditional probabilities	**Point estimates**	**Std. err.**	**[95% conf. interval]**	
Poor to poor	0.567	0.003	0.562	0.573
Poor to vulnerable	0.271	0.001	0.269	0.273
Poor to middle-class	0.162	0.002	0.158	0.166
Vulnerable to poor	0.150	0.002	0.146	0.155
Vulnerable to vulnerable	0.318	0.002	0.315	0.321
Vulnerable to middle-class	0.532	0.003	0.525	0.539
Middle-class to poor	0.017	0.000	0.016	0.018
Middle-class to vulnerable	0.089	0.001	0.087	0.091
Middle-class to middle-class	0.894	0.002	0.891	0.897
N	8,810			

Notes: Authors' calculations. Probabilities estimated using the national poverty lines provided in the household surveys and a vulnerability line obtained by setting the vulnerability index, P2, at 15% (see methodology section). Only the point estimates for poverty transitions obtained using the parametric approach are presented. The 'unconditional probabilities' panel provides the fraction of population in the selected age range that is in each of the nine categories. For example, 'Poor, poor' indicates the fraction of population that was poor in year 1 and poor in year 2. The 'conditional probabilities' panel provides the probability of each of the nine states. For example, 'Poor to poor' indicates the probability of being poor in year 2, given that the individual was also poor in year 1.

Figures

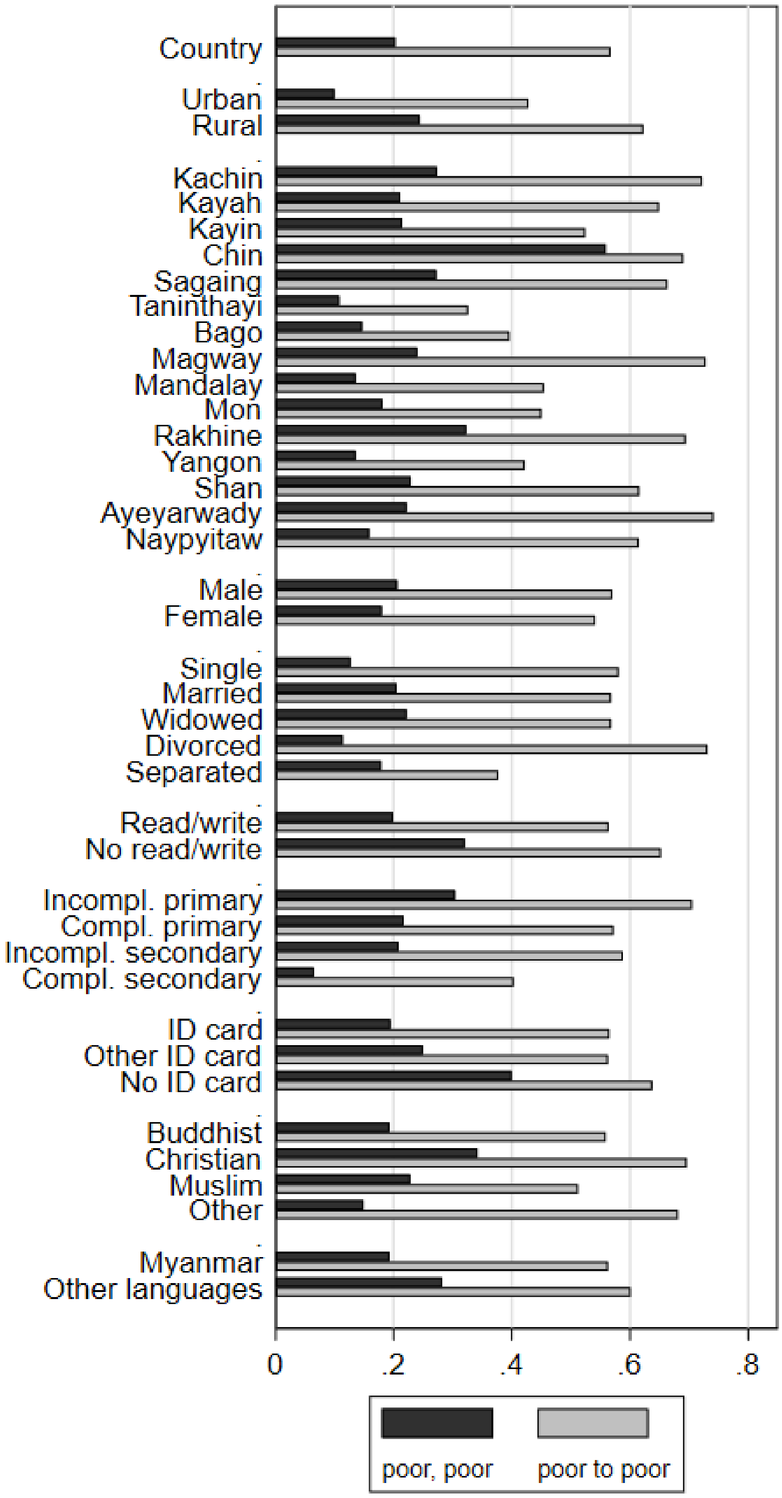
Figure 1: Poverty rates and GDP growth rates, 2005–19

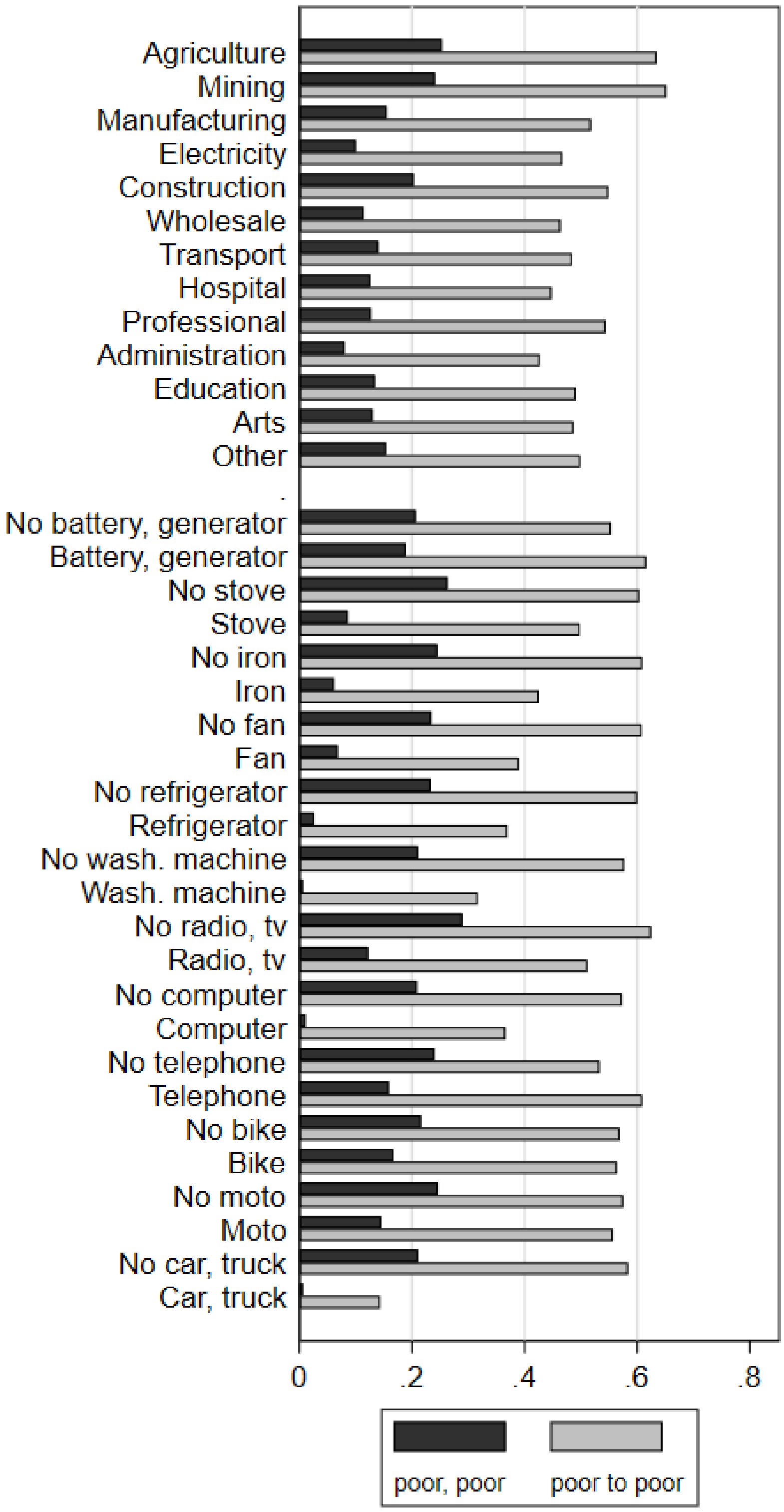


Data source: Authors' elaboration based on World Bank (2020b) and CSO, UNDP and World Bank (2018a; 2019).

Notes: The poverty rate in 2017 does not consider data from northern parts of Rakhine State (Maungdaw and Buthidaung townships) and the Wa Self-Administered Division, as it was not possible to survey households in these areas. See full documentation of limitations in coverage in the MLCS 2017 Technical Report (CSO, UNDP and World Bank, 2019a).

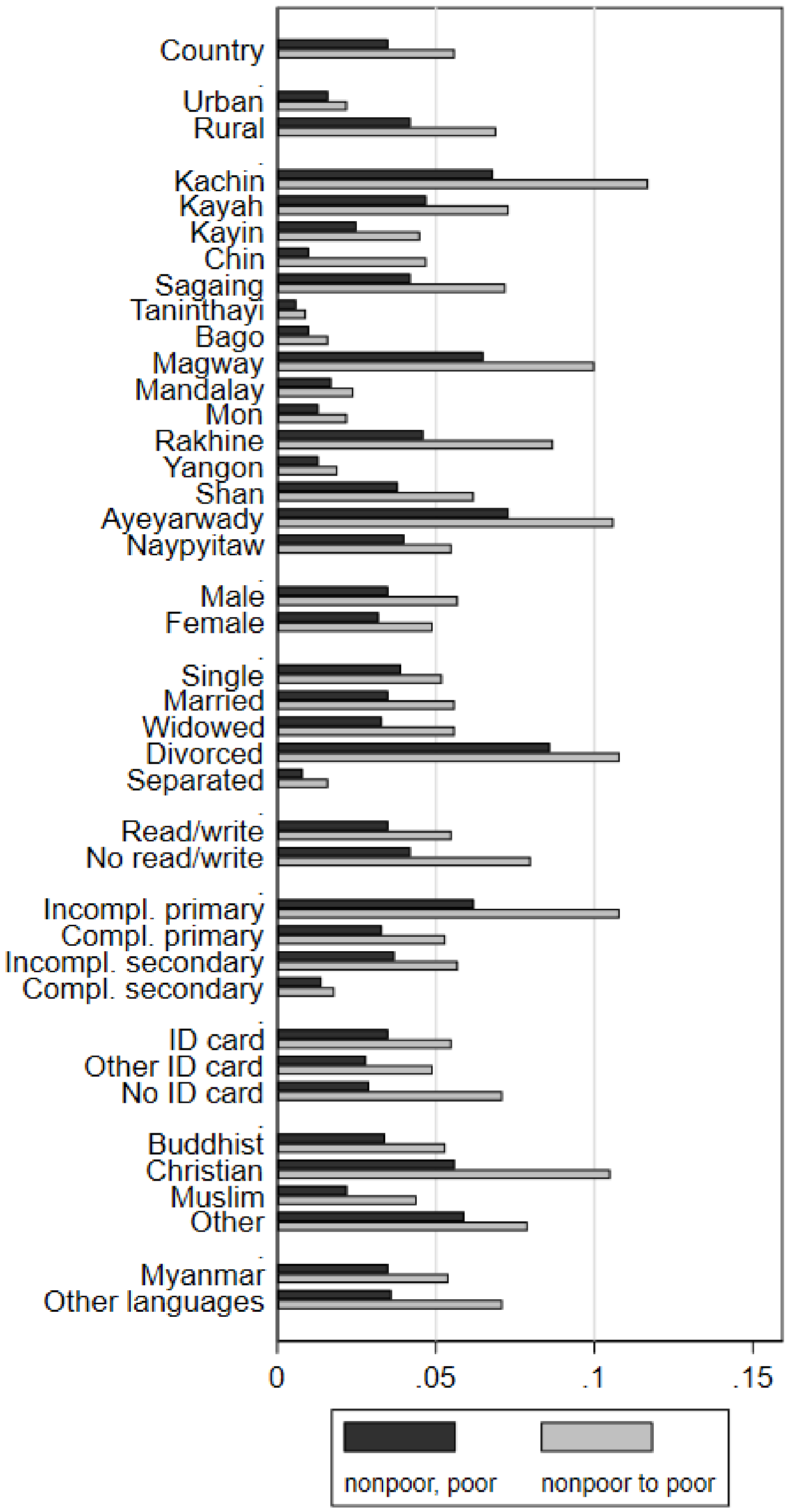
Figure 2: Unconditional probabilities of the state 'poor, poor', conditional probabilities of the state 'poor to poor' and household/location characteristics, 2015–17

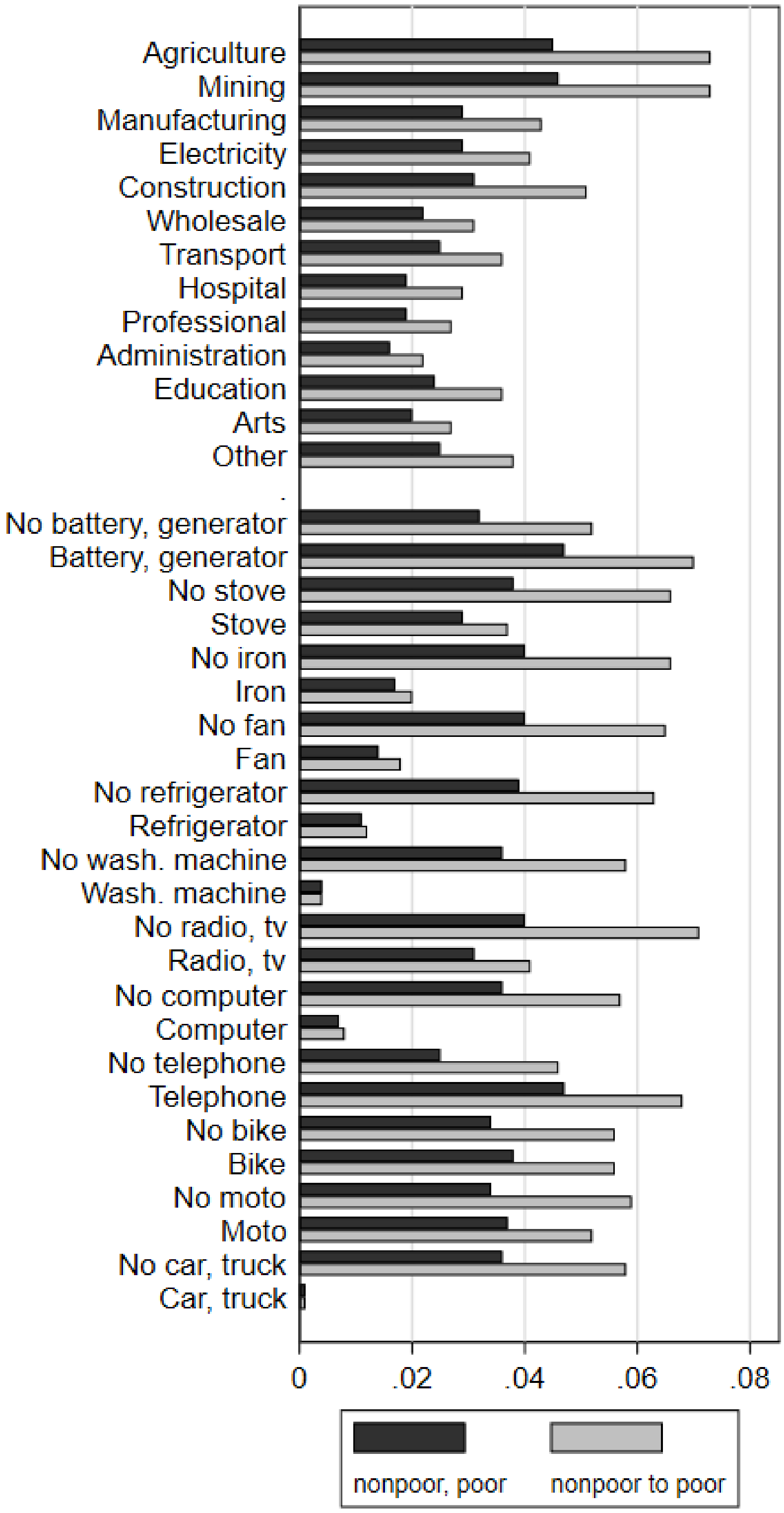




Notes: Authors' calculations. The probabilities presented are estimated using the national poverty lines provided in the household surveys. The figure provides the fraction of population in the selected age range that was poor in year 1 and poor in year 2 (state 'poor, poor'), and the probability of the state 'Poor to poor', which indicates the probability of being poor in year 2, given that the individual was also poor in year 1.

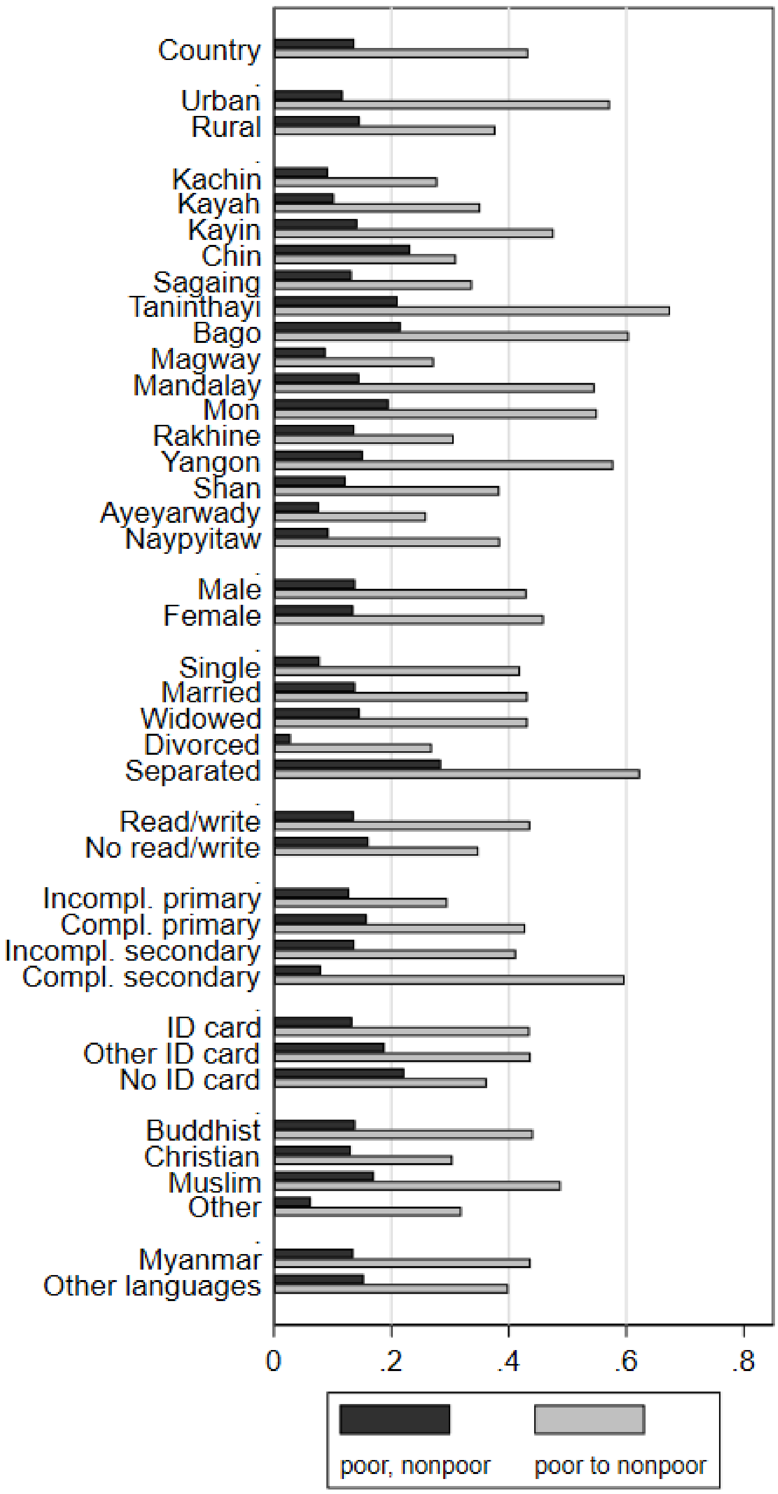
Figure 3: Unconditional probabilities of the state 'non-poor, poor', conditional probabilities of the state 'non-poor to poor' and household/location characteristics, 2015–17

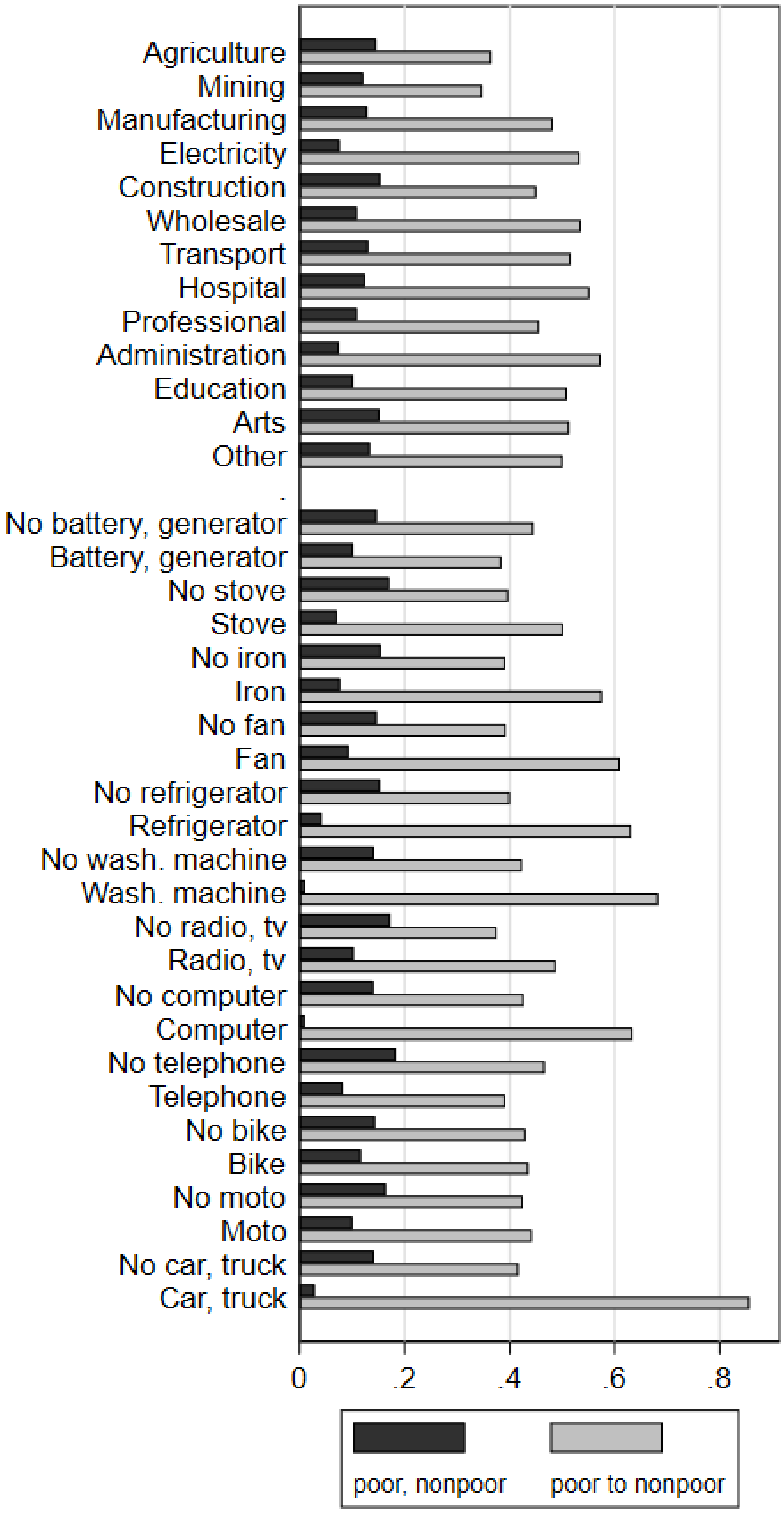




Notes: Authors' calculations. The probabilities presented are estimated using the national poverty lines provided in the household surveys. The figure provides the fraction of population in the selected age range that was non-poor in year 1 and poor in year 2 (state 'non-poor, poor'), and the probability of the state 'non-poor to poor', which indicates the probability of being poor in year 2, given that the individual was non-poor in year 1.

Figure 4: Unconditional probabilities of the state 'poor, non-poor', conditional probabilities of the state 'poor to non-poor' and household/location characteristics, 2015–17

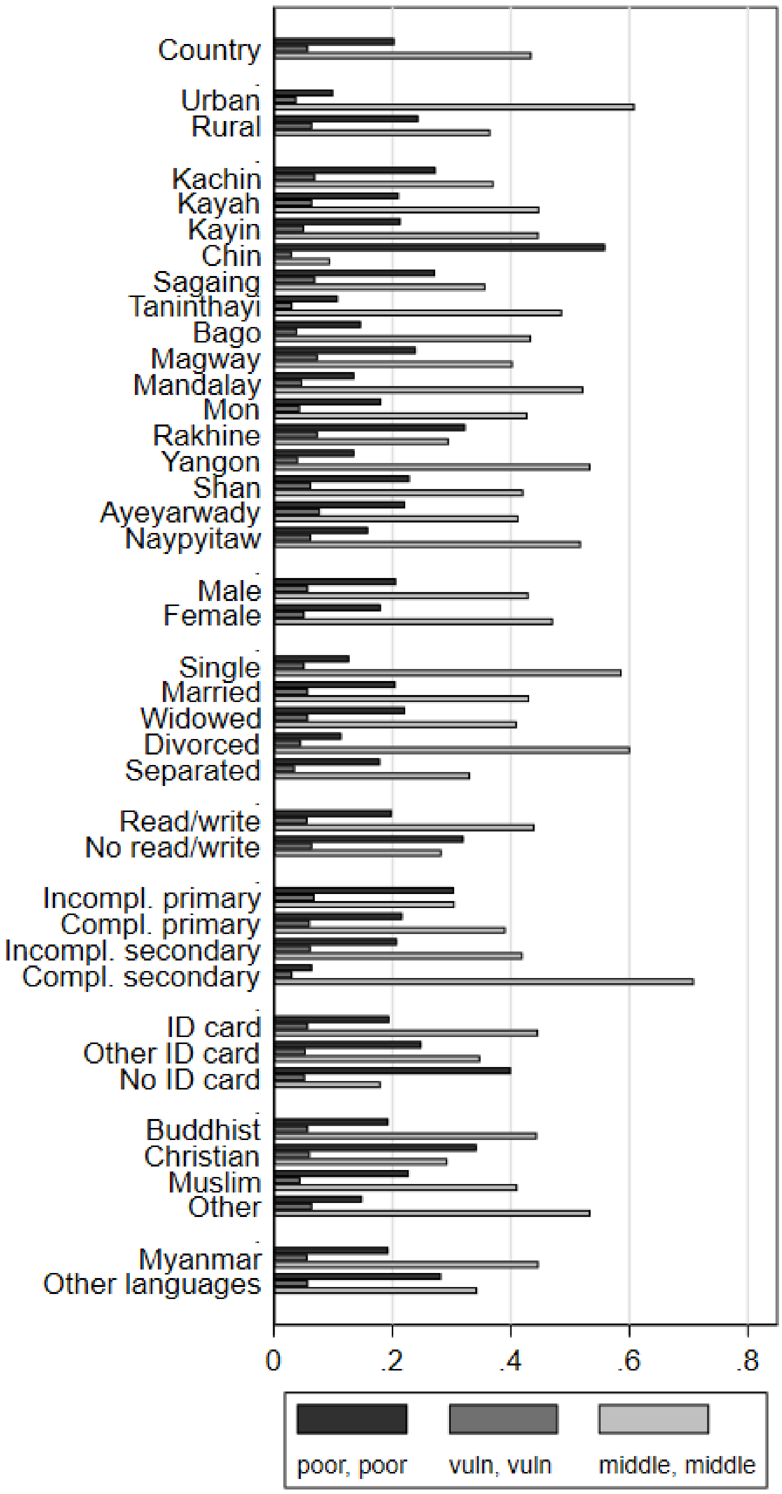


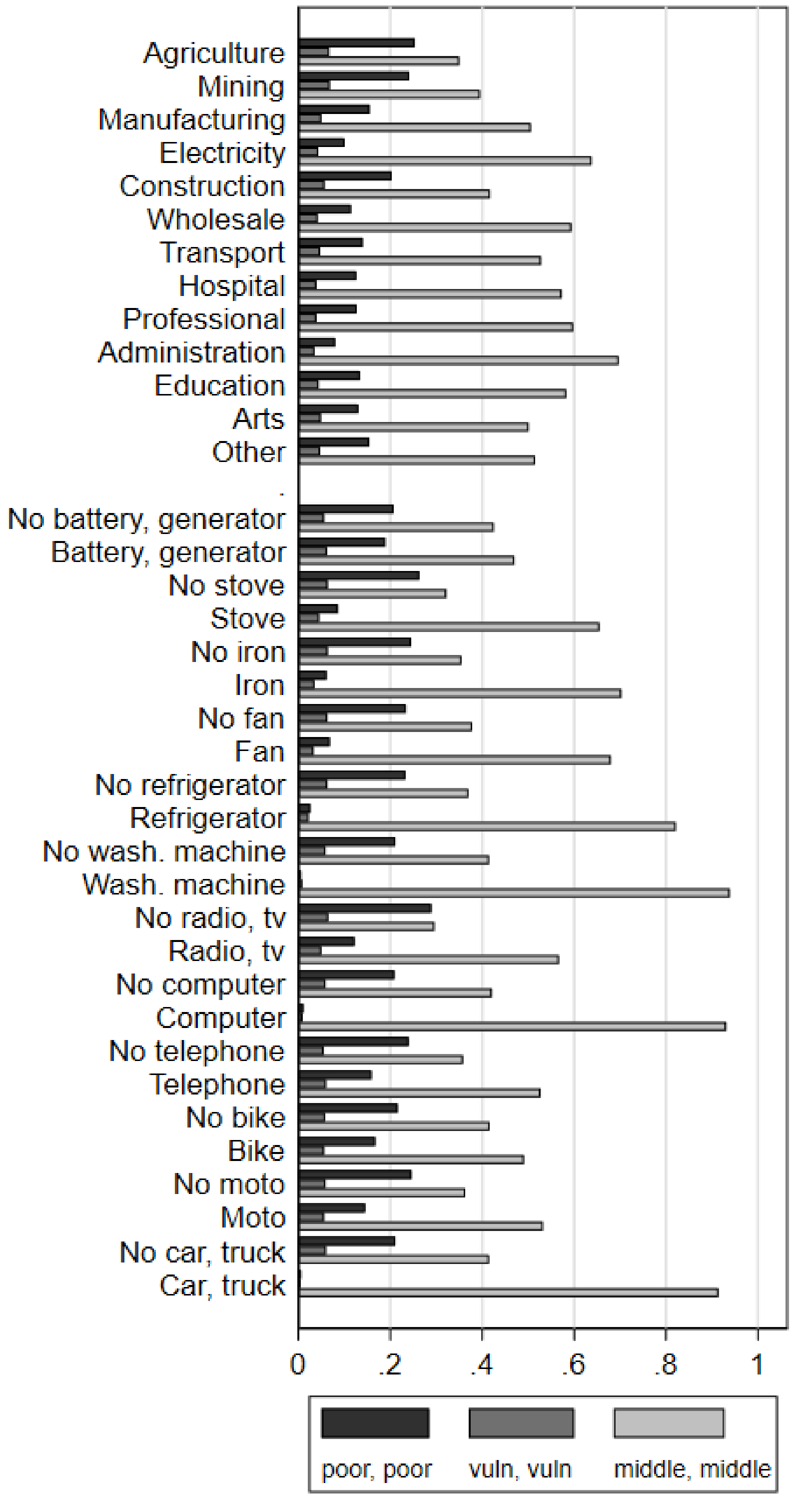


Notes: Authors' calculations. The probabilities presented are estimated using the national poverty lines provided in the household surveys. The figure provides the fraction of population in the selected age range that was poor in year 1 and non-poor in year 2 (state 'poor, non-poor'), and the probability of the state 'poor to non-poor', which indicates the probability of being non-poor in year 2, given that the individual was poor in year 1.

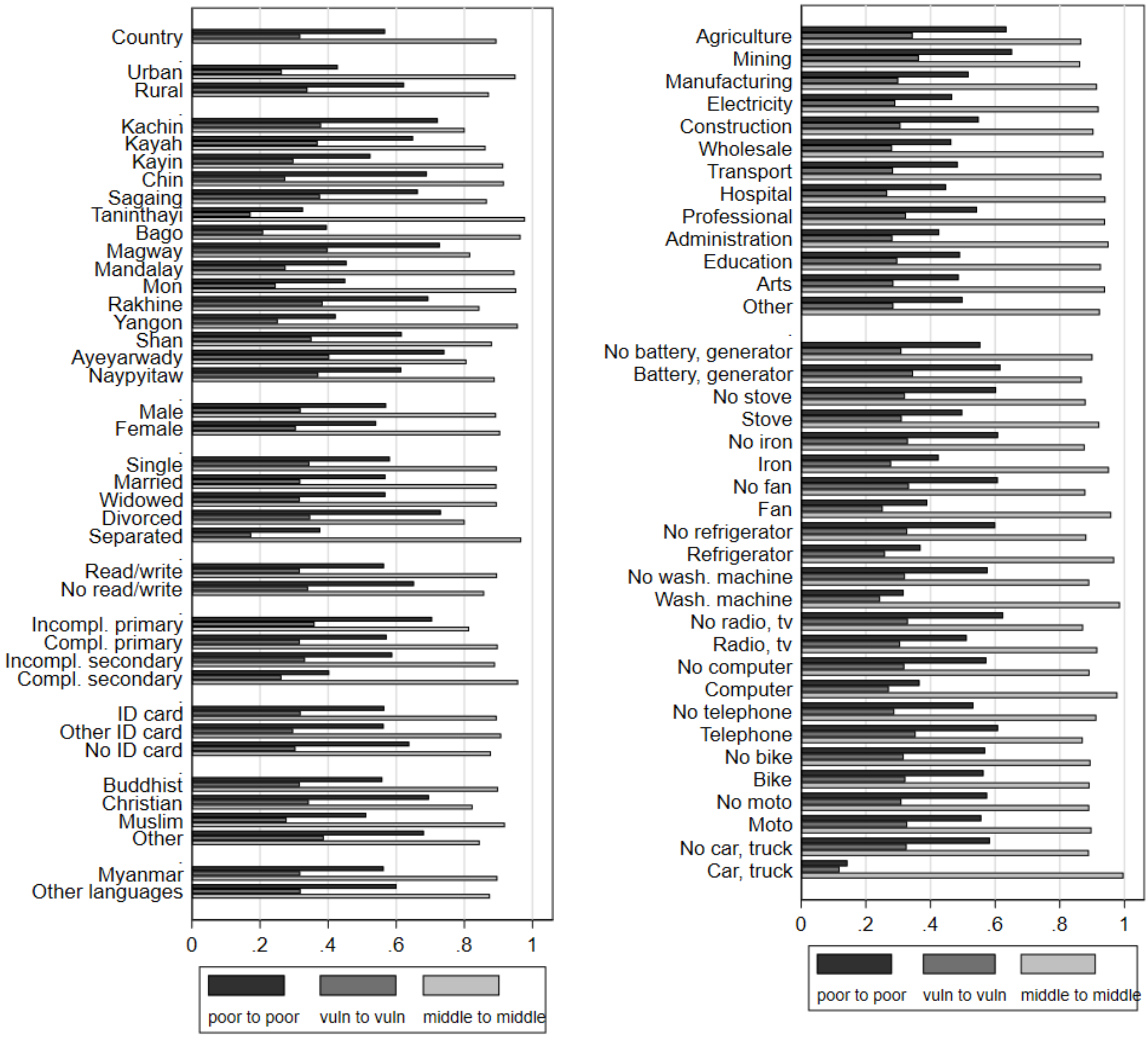
Figure 5: Unconditional probabilities of the states 'poor, poor', 'vulnerable, vulnerable' and 'middle-class, middle-class' (Panel a), conditional probabilities of the states 'poor to poor', 'vulnerable to vulnerable' and 'middle-class, middle-class' (Panel b), and household/location characteristics, 2015–17

Panel a




Agriculture
Mining
Manufacturing
Electricity
Construction
Wholesale
Transport
Hospital
Professional
Administration
Education
Arts
Other
No battery, generator
Battery, generator
No stove
Stove
No iron
Iron
No fan
Fan
No refrigerator
Refrigerator
No wash. machine
Wash. machine
No radio, tv
Radio, tv
No computer
Computer
No telephone
Telephone
No bike
Bike
No moto
Moto
No car, truck
Car, truck
0
.2
.4
.6
.8
1
poor, poor
vuln, vuln
middle, middle

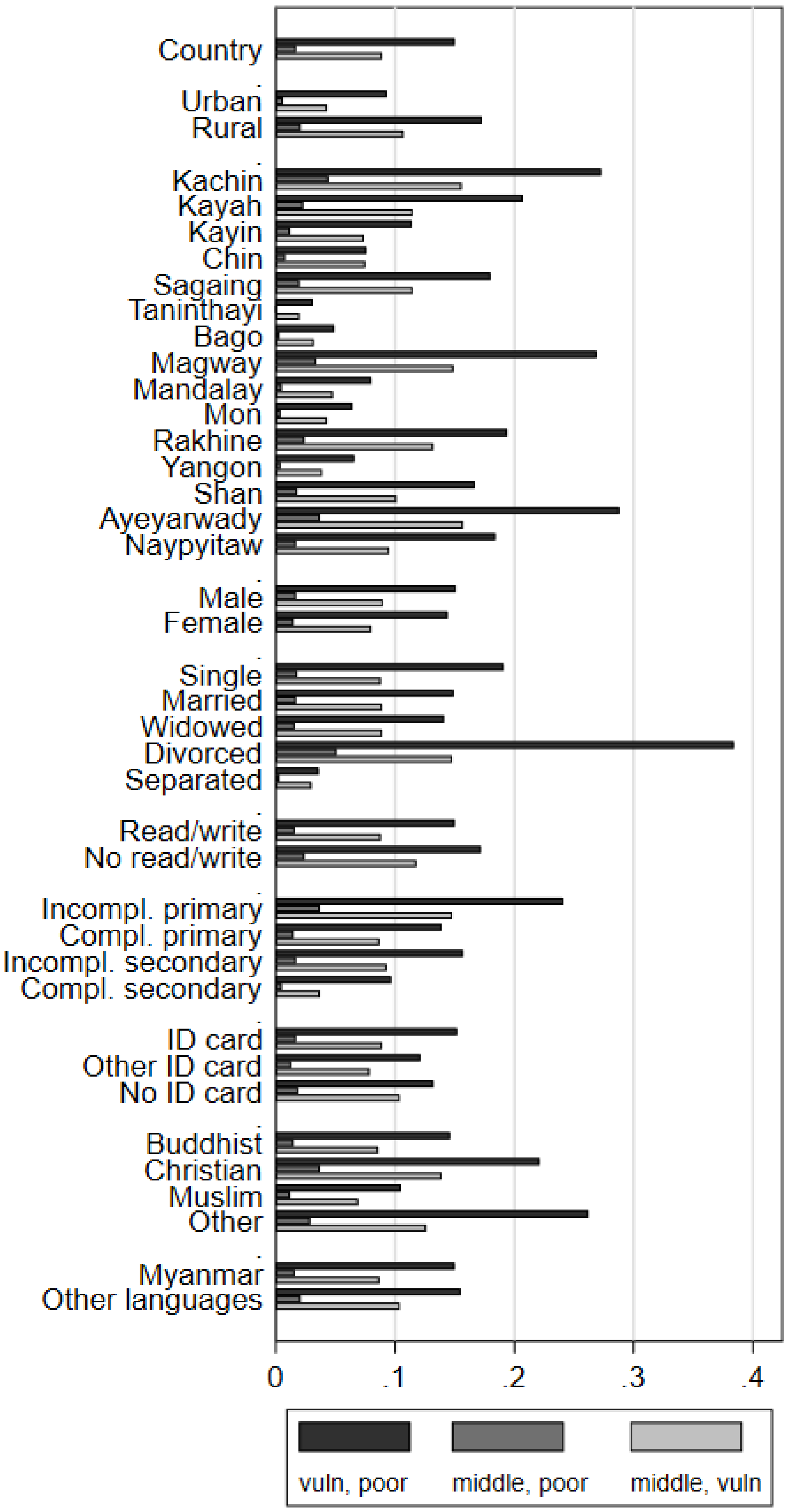
Panel b

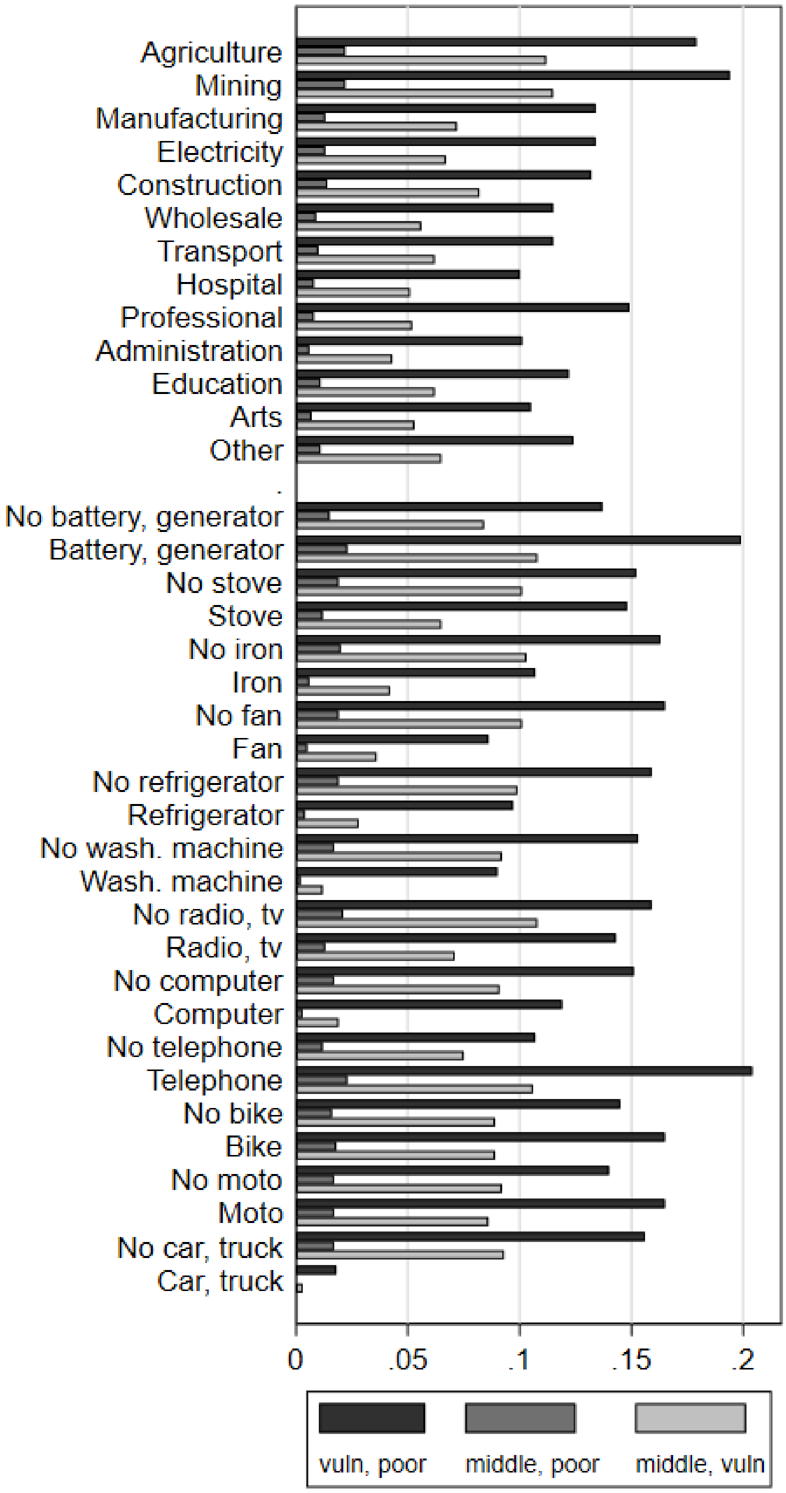


Notes: Authors' calculations. The probabilities presented are estimated using the national poverty lines provided in the household surveys and the vulnerability line computed here. Only the point estimates for poverty transitions obtained using the parametric approach are presented. The figure provides the fraction of population in the selected age range that was poor in year 1 and poor in year 2, and vulnerable in year 1 and vulnerable in year 2; it also provides the probability of being poor in year 2, given that the individual was also poor in year 1, and of being vulnerable in year 2, given that the individual was also vulnerable in year 1.

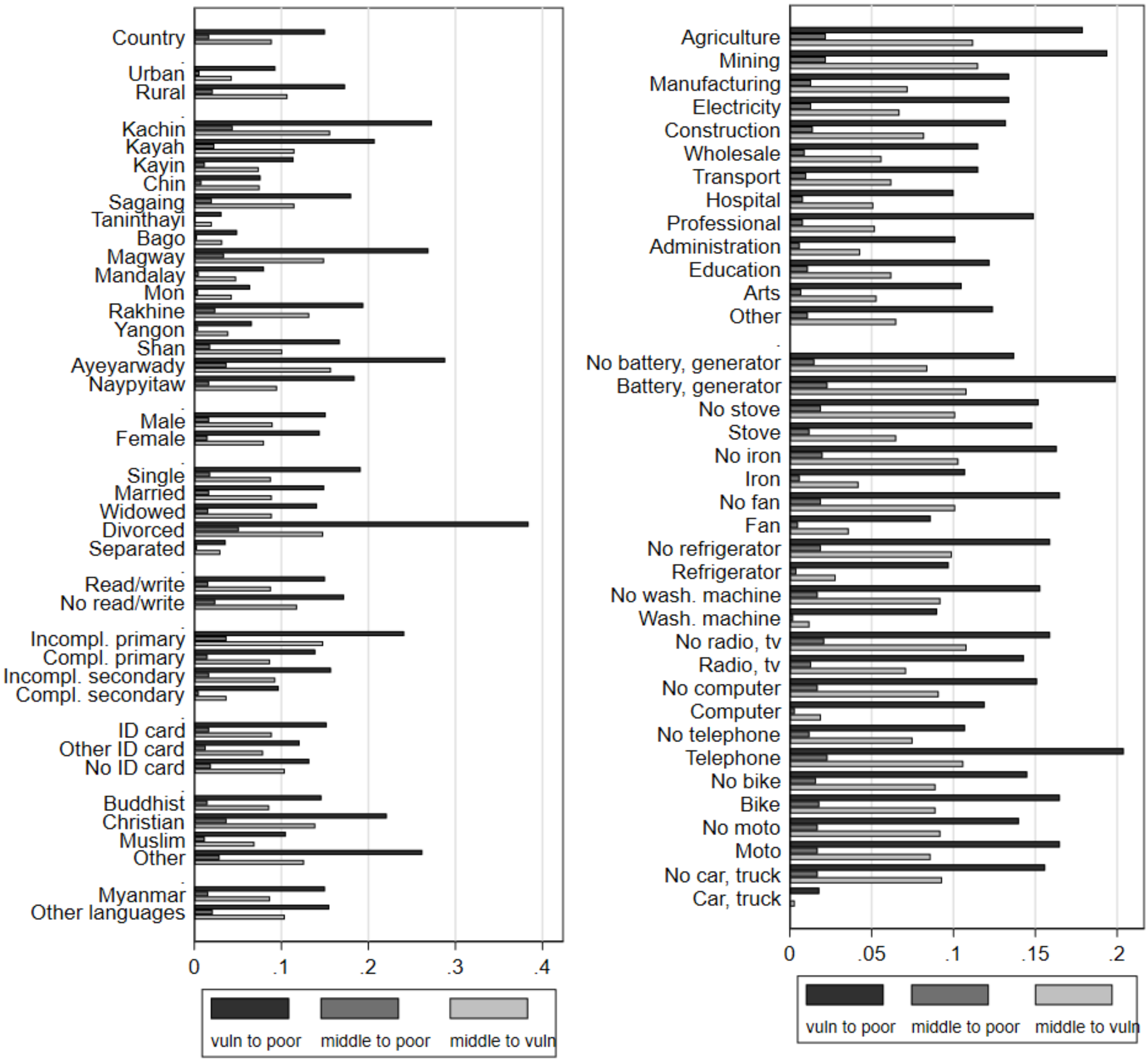
Figure 6: Unconditional probabilities of the states 'Vulnerable, poor', 'Middle-class, poor' and 'Middle-class, vulnerable' (Panel a), conditional probabilities of the states 'Vulnerable to poor', 'Middle-class to poor' and 'Middle-class to vulnerable' (Panel b), and household/location characteristics, 2015–17

Panel a




Agriculture
Mining
Manufacturing
Electricity
Construction
Wholesale
Transport
Hospital
Professional
Administration
Education
Arts
Other
No battery, generator
Battery, generator
No stove
Stove
No iron
Iron
No fan
Fan
No refrigerator
Refrigerator
No wash. machine
Wash. machine
No radio, tv
Radio, tv
No computer
Computer
No telephone
Telephone
No bike
Bike
No moto
Moto
No car, truck
Car, truck
0
.05
.1
.15
.2
vuln, poor
middle, poor
middle, vuln

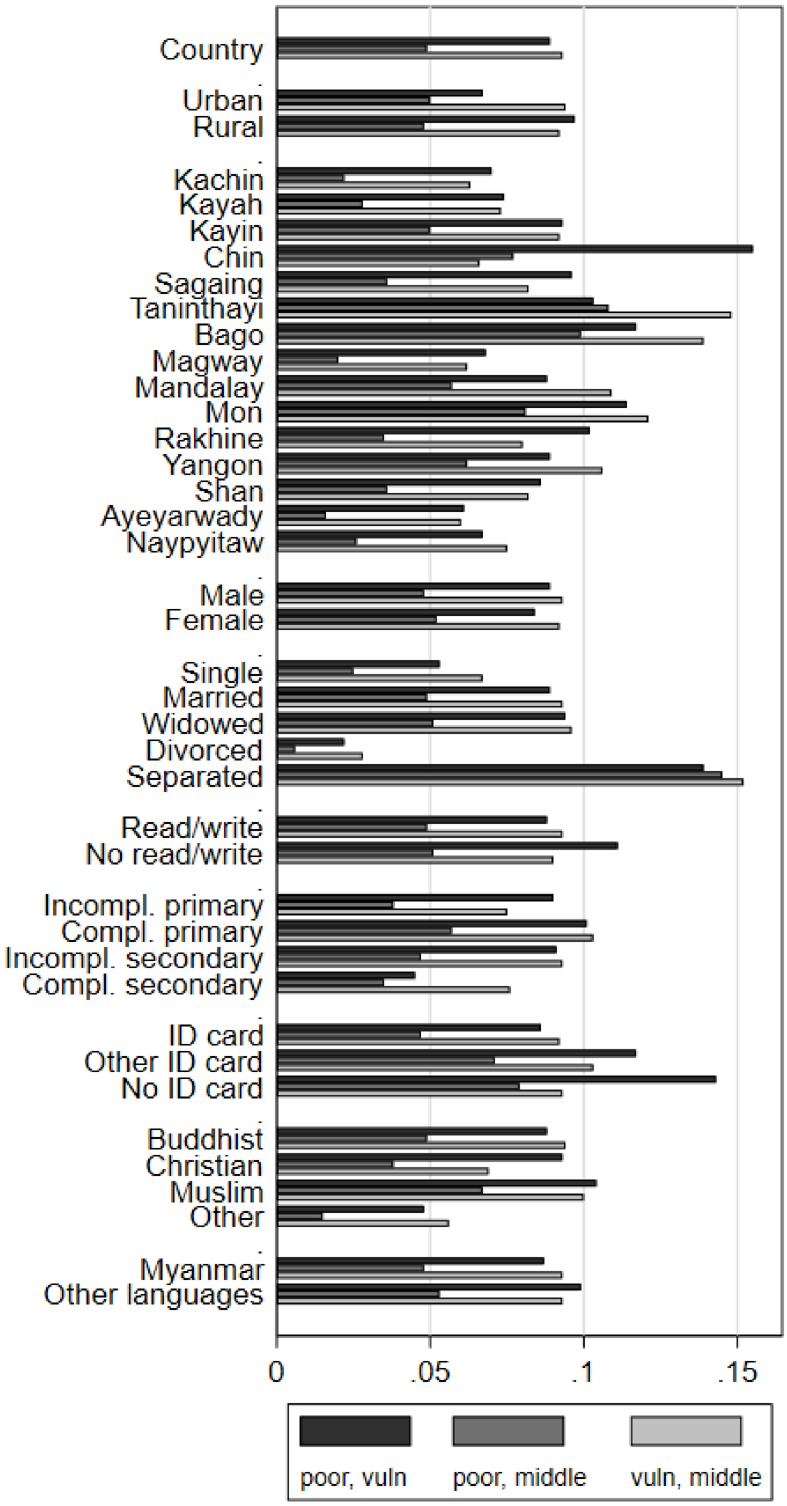
Panel b

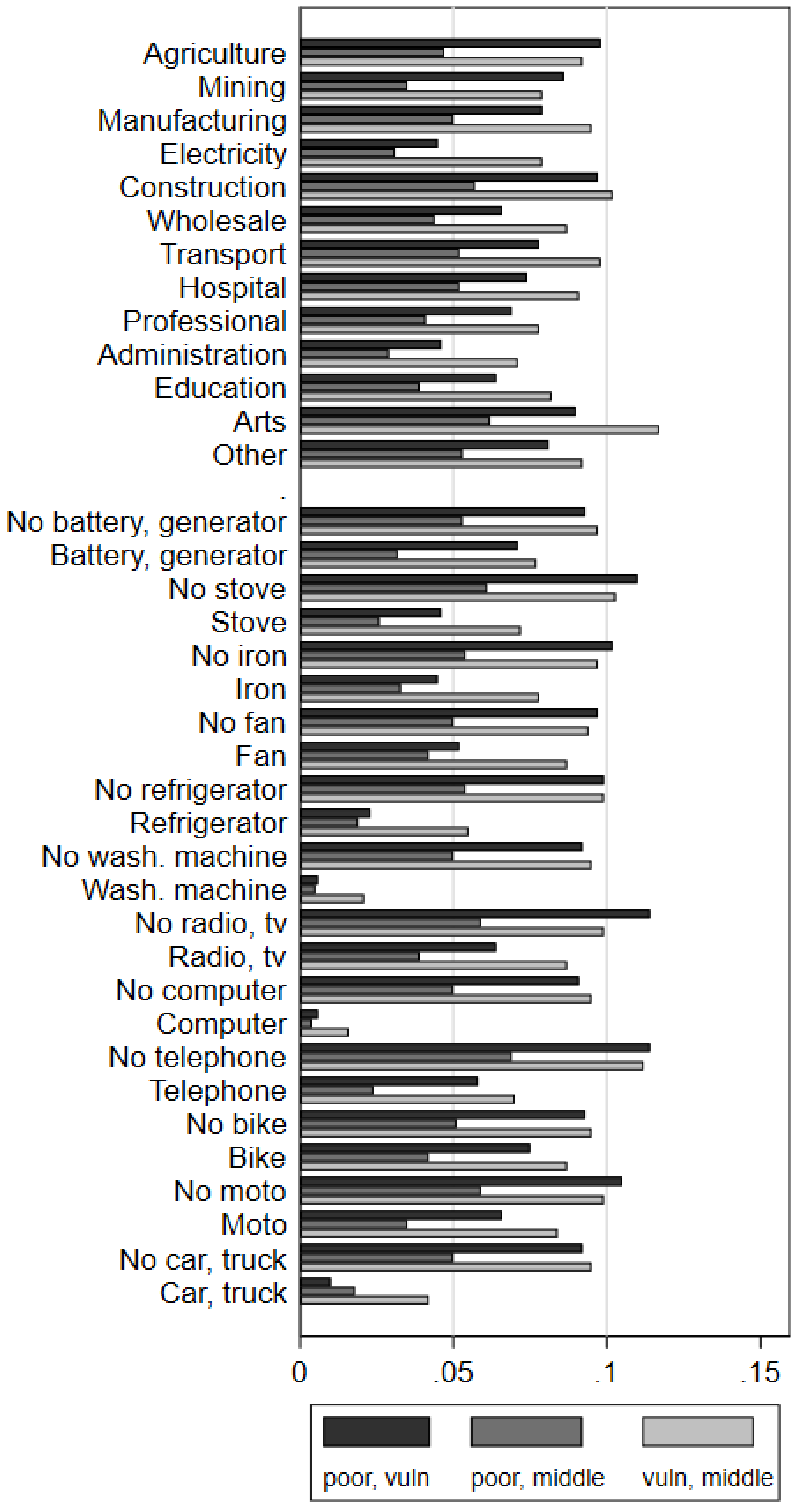


Notes: Authors' calculations. The probabilities presented are estimated using the national poverty lines provided in the household surveys and the vulnerability line computed here. Only the point estimates for poverty transitions obtained using the parametric approach are presented. The figure provides the fraction of population in the selected age range that was vulnerable in year 1 and poor in year 2, middle-class in year 1 and poor in year 2, and middle-class in year 1 and vulnerable in year 2; it also provides the probability of being poor in year 2, given that the individual was vulnerable in year 1, of being poor in year 2, given that the individual was middle-class in year 1, and of being vulnerable in year 2, given that the individual was middle-class in year 1.

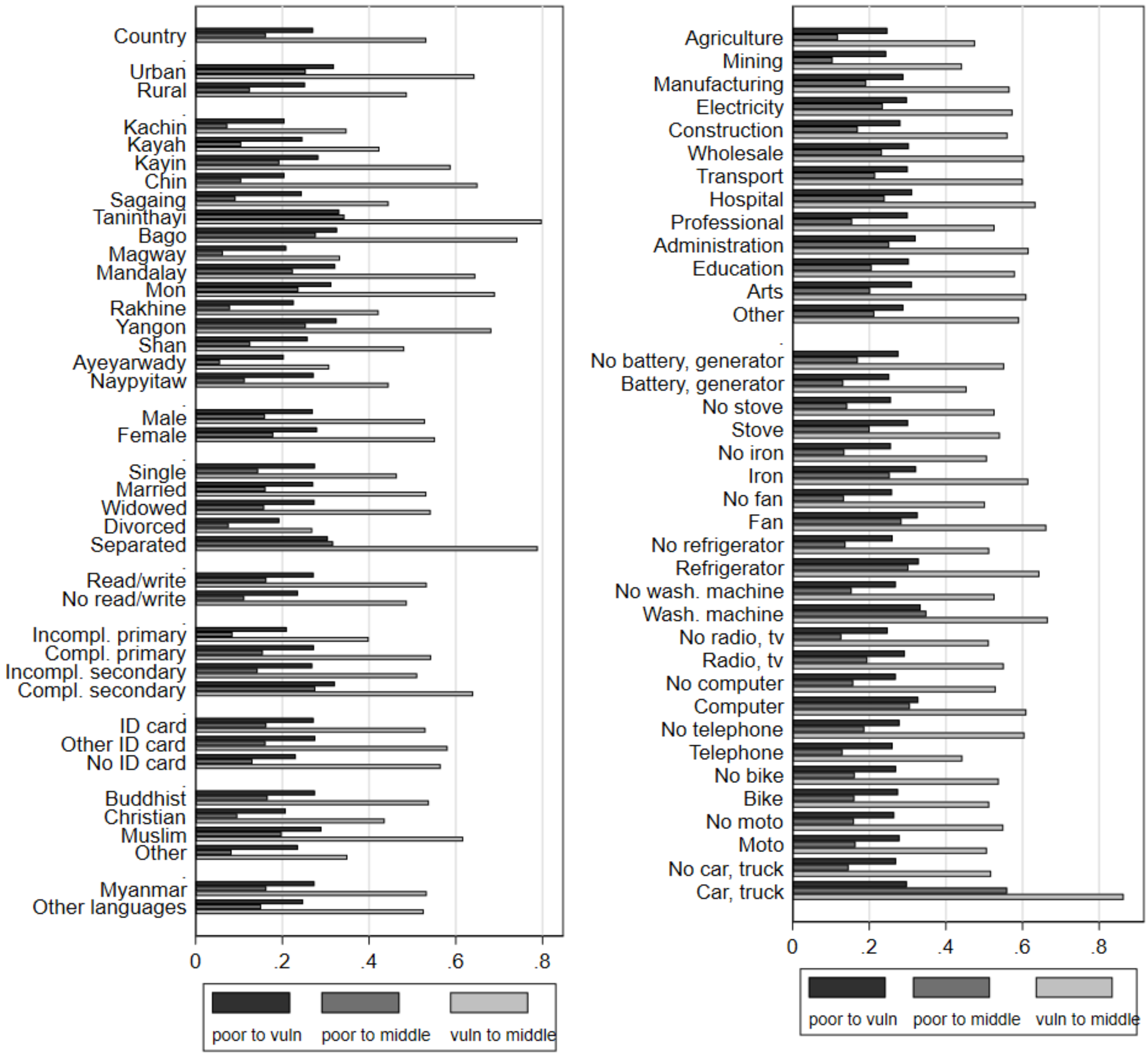
Figure 7: Unconditional probabilities of the states 'poor, vulnerable', 'poor, middle-class', and 'vulnerable, middle-class', (Panel a), conditional probabilities of the states 'poor to vulnerable', 'poor to middle-class', and 'vulnerable to middle-class' (Panel b), and household/location characteristics, 2015–17

Panel a




Agriculture
Mining
Manufacturing
Electricity
Construction
Wholesale
Transport
Hospital
Professional
Administration
Education
Arts
Other
No battery, generator
Battery, generator
No stove
Stove
No iron
Iron
No fan
Fan
No refrigerator
Refrigerator
No wash. machine
Wash. machine
No radio, tv
Radio, tv
No computer
Computer
No telephone
Telephone
No bike
Bike
No moto
Moto
No car, truck
Car, truck
0
.05
.1
.15
poor, vuln
poor, middle
vuln, middle

Panel b



Notes: Authors' calculations. The probabilities presented are estimated using the national poverty lines provided in the household surveys and the vulnerability line computed here. Only the point estimates for poverty transitions obtained using the parametric approach are presented. The figure provides the fraction of population in the selected age range that was poor in year 1 and vulnerable in year 2, poor in year 1 and middle-class in year 2, and vulnerable in year 1 and middle-class in year 2. Panel (b) provides the probability of being vulnerable in year 2, given that the individual was poor in year 1, of being middle-class in year 2, given that the individual was poor in year 1, and of being middle-class in year 2, given that the individual was vulnerable in year 1.

Appendix

Summary statistics

Table A1: Summary statistics, 2015–17

	2015					2017				
Variable	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
Real household consumption per adult equivalent	2,244	2017.8	1702.1	248.3	69226	8,810	2586.3	2116.3	262.9	97547
Household head's gender: Female	2,244	0.120	0.324	0	1	8,810	0.118	0.322	0	1
Household head's age	2,244	43.019	7.944	25	55	8,810	44.150	8.164	27	57
Marital status: Single	2,244	0.029	0.167	0	1	8,810	0.030	0.171	0	1
Marital status: Married	2,244	0.876	0.330	0	1	8,810	0.870	0.336	0	1
Marital status: Widowed	2,244	0.078	0.268	0	1	8,810	0.081	0.273	0	1
Marital status: Divorced	2,244	0.009	0.093	0	1	8,810	0.009	0.093	0	1
Marital status: Separated	2,244	0.009	0.095	0	1	8,810	0.010	0.100	0	1
Head cannot read and write	2,244	0.098	0.298	0	1	8,809	0.108	0.310	0	1
Educ level: Incomplete primary	2,050	0.156	0.363	0	1	8,001	0.137	0.343	0	1
Educ level: Complete primary	2,050	0.510	0.500	0	1	8,001	0.494	0.500	0	1
Educ level: Incomplete secondary	2,050	0.200	0.400	0	1	8,001	0.215	0.411	0	1
Educ level: Complete secondary	2,050	0.134	0.341	0	1	8,001	0.155	0.362	0	1
ID card: Citizenship scrutiny	2,244	0.857	0.350	0	1	8,810	0.926	0.262	0	1
ID card: Other types	2,244	0.046	0.210	0	1	8,810	0.023	0.149	0	1
ID card: No ID card	2,244	0.097	0.296	0	1	8,810	0.051	0.220	0	1
Religion: Buddhist	2,244	0.824	0.381	0	1	8,810	0.891	0.312	0	1
Religion: Christian	2,244	0.114	0.318	0	1	8,810	0.068	0.252	0	1
Religion: Muslim	2,244	0.041	0.198	0	1	8,810	0.027	0.162	0	1
Religion: Other	2,244	0.021	0.144	0	1	8,810	0.014	0.118	0	1

			2015					2017		
Mother tongue: Myanmar	2,244	0.640	0.480	0	1	8,810	0.855	0.352	0	1
Mother tongue: Kachin	2,244	0.017	0.129	0	1	8,810	0.003	0.059	0	1
Mother tongue: Kayin	2,244	0.065	0.247	0	1	8,810	0.012	0.108	0	1
Mother tongue: Chin	2,244	0.037	0.189	0	1	8,810	0.008	0.091	0	1
Mother tongue: Mon	2,244	0.016	0.124	0	1	8,810	0.003	0.056	0	1
Mother tongue: Rakine	2,244	0.046	0.209	0	1	8,810	0.045	0.208	0	1
Mother tongue: Shan	2,244	0.050	0.218	0	1	8,810	0.027	0.161	0	1
Mother tongue: Other	2,244	0.130	0.336	0	1	8,810	0.046	0.210	0	1
State/region: Kachin	2,244	0.027	0.163	0	1	8,810	0.037	0.189	0	1
State/region: Kayah	2,244	0.009	0.092	0	1	8,810	0.007	0.082	0	1
State/region: Kayin	2,244	0.024	0.153	0	1	8,810	0.029	0.167	0	1
State/region: Chin	2,244	0.015	0.121	0	1	8,810	0.012	0.107	0	1
State/region: Sagaing	2,244	0.087	0.281	0	1	8,810	0.101	0.301	0	1
State/region: Tanintharyi	2,244	0.030	0.169	0	1	8,810	0.029	0.167	0	1
State/region: Bago	2,244	0.108	0.311	0	1	8,810	0.103	0.304	0	1
State/region: Magway	2,244	0.073	0.260	0	1	8,810	0.070	0.255	0	1
State/region: Mandalay	2,244	0.119	0.324	0	1	8,810	0.109	0.311	0	1
State/region: Mon	2,244	0.032	0.176	0	1	8,810	0.033	0.178	0	1
State/region: Rakhine	2,244	0.066	0.248	0	1	8,810	0.061	0.240	0	1
State/region: Yangon	2,244	0.144	0.351	0	1	8,810	0.144	0.351	0	1
State/region: Shan	2,244	0.101	0.301	0	1	8,810	0.115	0.319	0	1
State/region: Ayeyarwady	2,244	0.151	0.359	0	1	8,810	0.128	0.334	0	1
State/region: Naypyitaw	2,244	0.016	0.125	0	1	8,810	0.024	0.153	0	1
Rural	2,244	0.740	0.439	0	1	8,810	0.731	0.444	0	1
Battery, inverter, generator	2,244	0.449	0.497	0	1	8,810	0.209	0.407	0	1
Stove, hotplate, cooker	2,244	0.343	0.475	0	1	8,810	0.321	0.467	0	1
Iron	2,244	0.205	0.404	0	1	8,810	0.211	0.408	0	1

	2015					2017				
Fan	2,244	0.164	0.371	0	1	8,810	0.174	0.379	0	1
Refrigerator	2,244	0.124	0.330	0	1	8,810	0.134	0.340	0	1
Washing machine	2,244	0.026	0.160	0	1	8,810	0.035	0.185	0	1
Radio, stereo, TV	2,244	0.613	0.487	0	1	8,810	0.494	0.500	0	1
Computer	2,244	0.025	0.156	0	1	8,810	0.025	0.156	0	1
Telephone	2,244	0.514	0.500	0	1	8,810	0.443	0.497	0	1
Bike	2,244	0.355	0.479	0	1	8,810	0.238	0.426	0	1
Moto	2,244	0.429	0.495	0	1	8,810	0.419	0.493	0	1
Motor vehicle	2,244	0.030	0.169	0	1	8,810	0.038	0.192	0	1

Notes: Authors' calculations. Summary statistics obtained with the restrictions imposed on the age of the household head (see methodology).

Consumption model

Table A2: Consumption model synthetic panel – Myanmar, 2015–17

Dependent variable: Log of household consumption per adult equivalent	2015	2017		2015	2017
Gender: Female	0.050	0.083	State/ region: Sagaing	-0.005	0.044
	(0.051)	(0.030)***		(0.092)	(0.059)
Household head's age	-0.003	-0.002	State/ region: Tanintharyi	0.193	0.492
	(0.002)*	(0.001)***		(0.099)*	(0.114)***
Marital status: Married	-0.164	-0.079	State/ region: Bago	0.088	0.309
	(0.065)**	(0.042)*		(0.094)	(0.059)***
Marital status: Widowed	-0.180	-0.123	State/ region: Magway	0.093	0.058
	(0.070)**	(0.044)***		(0.086)	(0.062)
Marital status: Divorced	0.142	-0.073	State/ region: Mandalay	0.055	0.203
	(0.107)	(0.093)		(0.088)	(0.058)***
Marital status: Separated	-0.283	0.003	State/ region: Mon	-0.049	0.165

Dependent variable: Log of household consumption per adult equivalent	2015	2017		2015	2017
	(0.122)**	(0.069)		(0.110)	(0.060)***
Head cannot read and write	-0.048	-0.034	State/ region: Rakhine	0.062	0.101
	(0.130)	(0.030)		(0.123)	(0.062)
Education level: Complete primary	0.000	0.101	State/ region: Yangon	-0.016	0.166
	(0.046)	(0.020)***		(0.083)	(0.056)***
Education level: Incomplete secondary	0.008	0.086	State/ region: Shan	-0.063	0.061
	(0.046)	(0.023)***		(0.103)	(0.060)
Education level: Complete secondary	0.130	0.250	State/ region: Ayeyarwady	0.256	0.147
	(0.057)**	(0.027)***		(0.095)***	(0.056)***
ID card: other types of	-0.105	-0.080	State/ region: Naypyitaw	0.207	0.184
	(0.096)	(0.066)		(0.120)*	(0.057)***
ID card: no	-0.200	-0.128	Rural	-0.036	-0.096
	(0.052)***	(0.035)***		(0.042)	(0.018)***
Religion: Christian	-0.108	-0.112	Battery, inverter, generator	0.080	0.024
	(0.083)	(0.037)***		(0.028)***	(0.016)
Religion: Muslim	-0.068	-0.011	Stove, hotplate, cooker	0.231	0.063
	(0.074)	(0.051)		(0.040)***	(0.017)***
Religion: Other	0.172	-0.055	Iron	0.054	0.022
	(0.117)	(0.080)		(0.039)	(0.021)
Mother tongue: Kachin	0.083	-0.190	Fan	-0.042	0.024
	(0.105)	(0.076)**		(0.043)	(0.020)
Mother tongue: Kayin	-0.101	-0.109	Refrigerator	0.200	0.175
	(0.094)	(0.039)***		(0.042)***	(0.023)***
Mother tongue: Chin	-0.156	-0.152	Washing machine	0.323	0.208
	(0.061)**	(0.057)***		(0.085)***	(0.036)***
Mother tongue: Mon	0.168	0.114	Radio, stereo, TV	0.117	0.104

Dependent variable: Log of household consumption per adult equivalent	2015	2017		2015	2017
	(0.107)	(0.056)**		(0.032)***	(0.016)***
Mother tongue: Rakine	0.071	-0.026	Computer	0.331	0.180
	(0.089)	(0.039)		(0.083)***	(0.044)***
Mother tongue: Shan	0.046	0.009	Telephone	0.146	-0.009
	(0.082)	(0.066)		(0.031)***	(0.013)
Mother tongue: Other	-0.077	-0.112	Bike	0.009	-0.012
	(0.063)	(0.098)		(0.026)	(0.014)
State/ region: Kayah	0.080	0.131	Moto	0.161	0.113
	(0.156)	(0.060)**		(0.032)***	(0.015)***
State/ region: Kayin	0.009	0.152	Motor vehicle	0.335	0.549
	(0.114)	(0.058)***		(0.079)***	(0.042)***
State/ region: Chin	-0.292	-0.047	Constant	7.525	7.550
	(0.113)***	(0.071)		(0.139)***	(0.076)***
Adjusted R-squared	0.441	0.366			
N	2,050	7,656			

Note: Authors' calculations. Restrictions imposed on age of the household head (see methodology). * p<0.1; ** p<0.05; *** p<0.01.