

# Alternative prediction models for measuring material deprivation to poverty in an environment of scarce data

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## Abstract

The prevailing practice of defining classes of material deprivation is based on the sum of a small number of binary items. While this approach has obvious advantages in terms of communication and ease of use, it is limited to an ordinal measure of deprivation. We propose a probabilistic approach to identifying deprived individuals, treating deprivation as a latent construct that can be measured using a set of observable indicators. In an initial attempt to measure material deprivation in Southeast Asian countries (ASEAN), we emulated the EU’s approach of selecting indicators covering several aspects of people’s welfare. These range from an inability to afford basic necessities for a decent standard of living to a lack of essential utilities, such as water and electricity. This paper uses the latest available wave of the Asian Barometer Survey to estimate comparable prevalence rates of material deprivation in Vietnam, Thailand, Indonesia, Malaysia and Myanmar. A set of eleven observable indicators that are common to the five selected countries is considered. Our results reveal significant disparities between these countries. Deprivation rates range from 11% in Malaysia to 74% in Myanmar, highlighting the need for country-specific policy interventions to mitigate risks. On average, deprivation rates are underestimated using the traditional counting approach. Finally, we model individual deprivation traits as a function of individual characteristics and contextual factors.

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*Keywords:* Material deprivation, Latent variable measurement model, Asian Barometer Survey.

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# 1 Introduction

Traditionally, poverty is defined as an individual's or household's inability to afford basic necessities such as food and shelter. They are commonly obtained through market purchases or self-provision. Therefore, the lack of monetary resources (income or consumption expenditures at market prices) has been the prevailing way to measure poverty. A consequence of the lack of resources is that a poor individual will eventually become materially deprived, that is, they will not be able to "have the living conditions and amenities which are customary, or at least widely encouraged or approved, in the society to which they belong" (Townsend, 1979, p.31). In this view, the lack of resources anticipates poverty, and material deprivation is the direct consequence of the lack of resources. The relevance of material deprivation stems from its characteristic as an outcome measure, which puts specific emphasis on the living conditions attained by a household. The rationale behind analyzing material deprivation is that monetary-based indicators alone are considered insufficient to accurately reflect the diversity of living conditions, especially in markets that do not function well.

Therefore, measuring material deprivation is crucial for understanding and addressing poverty, particularly in developing countries, as it provides a more nuanced understanding of poverty than income-based measures do. This is because it highlights the specific deprivations that individuals and households face daily. In fact, relying solely on income-based poverty lines, which is quite common in poor countries, may not accurately reflect the lived experience of deprivation. Even with a certain income level, individuals may still face significant hardship. This approach, often referred to as multidimensional poverty, accepts that poverty encompasses more than just a lack of income; it also includes the inability to afford necessities and participate in social life (see among others Bossert et al. 2013). Therefore, it is necessary to have a composite measure that captures the wide range of deprivation characteristics. This involves acknowledging the latent nature of material deprivation and the various indicators of the composite measure and its empirical manifestation.

When material deprivation is considered a latent variable, the set of items acts as a measurement instrument (or scale) that can capture the complex nature of deprivation. We use Item Response Theory's latent variable measurement approach to obtain a numerical measure of deprivation from these items in a set of Southeastern Asian countries (ASEAN).

According to the Socio Cultural Community Trend Report (2025), eradicating poverty in the Southeast Asian Nations is still a priority. In fact, while China has made significant progress in eliminating poverty, South and Southeast Asia have lagged behind (Silber and Wan, 2016). However, the way poverty is conceptualized and measured

varies across the ASEAN region. ASEAN member states use different methods and include different indicators to measure poverty. This variety of measurements reflects contextual differences among member states but undoubtedly complicates the development of a standardized regional framework for comparing progress across ASEAN countries. Moreover, global standards fail to capture the complex cultural and social dimensions of poverty in ASEAN, where poverty reflects non-income factors (Beard, 2019), and traditional global standards are insufficient for establishing inclusive poverty alleviation initiatives that consider multiple dimensions.

A further complication arises from the fact that most studies on poverty in the ASEAN region rely on household survey data collected by national statistical agencies. The resulting estimates are often flawed because they depend on whether income or expenditure data are used, as well as on whether and how adjustments are made for household size. This problem becomes even more acute when making cross-country comparisons (Both, 2019). To supplement income- or expenditure-based poverty estimates, and more importantly, to overcome data scarcity and lack of comparability, this paper attempts to measure material deprivation in ASEAN countries using data coming from the most recent wave of the Asian Barometer Survey (ABS), which is a cross-national, comparative survey that focuses on socioeconomic modernization, regime transitions, and democratization across the ASEAN region.

This paper is not the first to use ABS survey data. In fact, Deutsch et al. (2020) used asset ownership data from the Asia Barometer Survey to provide comparable poverty and inequality rates in six ASEAN member economies for 2014 and 2016. Relying on standardized ABS data, we estimated meaningful, comparable material deprivation rates for 2019 in Cambodia, Indonesia, Malaysia, Myanmar, Thailand, and Vietnam.<sup>1</sup> Estimation is performed within a multidimensional setting using a probabilistic approach.

Although ABS survey data are standardized and information is gathered using the same questions, wording, and format for all respondents, it can still be somewhat problematic to provide comparable estimated deprivation rates across different cultural and economic contexts. To ensure a sufficient level of comparability, we calibrate the deprivation measure to a common metric using a simple equating procedure.

The paper is organized as follows. Section 2 discusses the different approaches for measuring material deprivation in the literature. Section 3 provides an introduction to the latent approach to measurement, highlighting the main advantages and disadvantages of more traditional approaches. Using data from the ABS survey, section 3.1 describes and discusses how to estimate material deprivation using a latent model-based approach. Comparability of prevalence rates across countries is ensured by de-

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<sup>1</sup>The selection of these five countries was based on data availability.

tecting differential item functioning and adjusting country-specific thresholds through a calibration procedure. Finally, section 4 compares the prevalence rates of material deprivation in the selected Eastern Asian countries with the rates based on the well-established counting approach, and provides an exploratory analysis of the predictors of deprivation at individual and regional level. Conclusions are drawn in section 5.

## 2 From counting to a latent approach

Non-monetary measures of material deprivation have been proposed by Eurostat and widely applied in EU countries (Eurostat, 2012). The fundamental assumption is that the severity of deprivation condition of a household or an individual cannot be observed directly, but its measure can be inferred from observable deprivation indicators (items) that have the same response format (0 if the individual is deprived on that item or 1 if the individual is not deprived on that item). Each individual is assigned a set of attributes or items representing different aspects of living conditions. In order to measure deprivation, it is necessary to check whether an individual possesses a minimum acceptable number of these attributes. These quantities represent the threshold limits necessary for an adequate standard of living. The ability to deal with such discrete response data is fundamental, since only few variables measuring individual well-being are numerical in nature. This is the case of material deprivation, where each attribute represents a deprivation item, and an affirmative response indicates a basic necessity failure.

Traditionally, material deprivation is defined and those who are deprived are identified using a “counting approach,” somehow similar to the multidimensional poverty approach of Alkire and Foster (2011). This approach is based on classical test theory (CTT) and involves the following steps:

1. Selection of relevant indicators to cover the different aspects of deprivation. These items represent a measurement scale, which is a process that transforms a set of observable indicators into numbers representing the magnitude of the latent variable (deprivation). Ideally, the items should cover a wide range of severity levels; therefore, low-, medium- and highly-severe items should be included in the list of plausible indicators.
2. Codification of each indicator into a binary variable (item). Typically, binary scores are in the form of ‘yes’ or ‘no’. They indicate whether a certain item is affordable or unaffordable.
3. Construction of a deprivation index calculated as the sum (possibly weighted) of the affirmative responses, which is then converted into a raw score.

4. Identification of deprived individuals. This is done by looking at their raw score. An individual is identified as deprived when his/her raw score must be equal to or greater than a fixed cut-off.

More formally, given a population of  $N$  individuals, and  $D$  items of deprivation,  $d_{is}$ ,  $i \in \{1, \dots, N\}$  and  $s \in \{1, \dots, D\}$  is defined as:

$$d_{is} = \begin{cases} 1 & \text{if individual } i \text{ is deprived in item } s \\ 0 & \text{otherwise.} \end{cases}$$

The deprivation assessment for individual  $i$  is the sum of their positive items (deprivations), yielding the deprivation raw score  $RS_i = \sum_{s=1}^D d_{is}$ . Deprived individuals are defined as those lacking a certain number of items. This definition requires the identification of a threshold. This threshold is a positive integer  $k$ , which denotes the minimum number of items an individual cannot afford to be classified as deprived/poor. Having fixed  $k$ , each individual is either deprived/poor or not deprived/poor according to the following crisp identification:

$$\text{deprived}_i^{(k)} = \begin{cases} 1 & \text{if } RS_i \geq k, \\ 0 & \text{if } RS_i < k. \end{cases}$$

Potentially, the deprivation threshold  $k$  may take all values in the range  $k = 1, \dots, D$ .<sup>2</sup> For a given  $k$ , the proportion of the population that fails to meet the minimum standard is referred to as the incidence of deprivation, or prevalence rate, defined as:

$$PR_k = \frac{\sum_{i=1}^N \text{deprived}_i^{(k)}}{N} = \frac{q_k}{N}. \quad (1)$$

The “sum-score” scale is straightforward to construct and interpret. However, a critical disadvantage is that it is treated as a numerical measure. Even when expressed numerically, raw scores provide only an ordinal measure of deprivation: the difference in intensity between two adjacent raw scores is not necessarily constant. Using an ordinal measure, we can say that individuals with a raw score of 4 are more deprived than individuals with a raw score of 2, but we do not know the exact difference between these two individuals. The measure is also constrained to lie between 0 and a ceiling represented by the maximum number of items. According to CTT, a person’s level of deprivation depends strictly on the items that form the scale (Farcomeni et al., 2024). If the scale consists only of severe items, respondents must have a high level of deprivation to respond “not to afford.” Item severity refers to the level of deprivation required to respond affirmatively to an item. For instance, the likelihood of residing in

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<sup>2</sup>According to the EU’s material deprivation methodology, individuals are considered to be at risk of severe material deprivation if they cannot afford at least seven out of thirteen items.

a dwelling without basic infrastructure depends on the individual's level of deprivation and the item's severity. Consequently, unless the poor are extremely poor, respondents will report low scores, meaning the level of poverty in society will be deemed very low. Furthermore, these reported scores underestimate the true level of poverty, since individuals are generally not deprived, but unable to afford the most expensive items. In this way, the level of deprivation experienced by an individual depends on the severity of the items included in the scale and is therefore not 'test-free'. Similarly, the measurement scale itself is not 'person-free', in that item severity depends strictly on the level of deprivation experienced by the group of respondents. In fact, the CTT makes no inherent assumptions about the severity of the included items.

Based on Item Response Theory (IRT), the latent approach provides a rationale for mapping binary responses onto a numerical scale following a probabilistic scheme. Deprivation is viewed as a hidden continuum with magnitudes increasing in a given direction that can be indirectly measured using observable deprivation items (see among others, Whelan and Maître (2006); Cappellari and Jenkins (2007); Deutsch et al. (2015); Nájera Catalán. (2027); Dotto et al. (2019)). Within this approach, the probability of being deprived in each item depends on both individual and item characteristics and it is a monotonically decreasing function of the latent trait that the items measure. Therefore, with respect to the counting approach, individual severity<sup>3</sup> and item severity are here intrinsically related and no longer independent. The latent approach establishes an order of items based on their estimated severity. Consequently, the most deprived individuals are more likely to respond positively to the most severe items than those who are less deprived. It is important that the items comprising the scale have adequate power to discriminate between low and high levels of deprivation among individuals (item discrimination), thus ensuring that individuals are correctly ranked according to their estimated underlying trait.<sup>4</sup>

In the counting approach, an individual's raw score is, at best, an ordinal measure of deprivation. In contrast, within the latent approach, an individual's estimated severity is an interval-level measure of deprivation. This allows for a more accurate assessment of relative differences in deprivation intensity between individuals with each raw score along the scale. The estimation of individual severity follows the simplest IRT model, equivalent to the Rasch model, which converts counts into linear measures through a logistic transformation. The resulting estimate satisfies the specific objectivity property and establishes a ranking of items based on their estimated severity. The property of specific objectivity ensures that the measurement scale is 'test-free' and 'person-free'.

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<sup>3</sup>The term individual severity describes the personal intensity (level) of deprivation along the hidden continuum scale.

<sup>4</sup>Items with low level of discrimination power are ambiguously worded and often removed.

This implies that comparisons between respondents are independent of the particular items used and that comparisons of items are also independent of respondents. This property constitutes a significant component of the Rasch measurement, yet it does not align with the principles underlying the counting approach. The next section will go into more detail about the Rasch model and how to estimate its parameters.

### 3 Model, data and estimation strategy

#### 3.1 The Rasch model

Within the Item Response Theory (IRT) framework, the Rasch model (Rasch, 1960) is the simplest measurement model that preserves all the desirable properties of a measurement scale. This model estimates the probability that respondent  $i$  will report the inability to cope with a item  $j$  ( $y_{ij}$ ) as a logistic function of the distance between the respondent's and the item's positions on the severity scale:

$$\text{Prob}\{Y_{ij} = 1|\beta_i\} = \frac{e^{(\beta_i - \delta_j)}}{1 + e^{(\beta_i - \delta_j)}}, \quad (2)$$

where  $\beta_i$  (the severity of the respondent's deprivation) is the position of individual  $i$  on the latent trait and  $\delta_j$  (the item severity parameter) the position of item  $j$ . When applying the model to measure deprivation, the  $\delta$  parameters are interpreted as reflecting the severity associated with the experience of deprivation captured by the different items, while the  $\beta$  parameters are interpreted as measuring the intensity of deprivation experienced by the respondents. Both  $\beta_i$  and  $\delta_j$  are measured on the same scale and lie on  $\mathbb{R}$ .<sup>5</sup> The conditional probability of affirming any item  $j$  is a monotonic non decreasing function of the individual level of deprivation  $\beta_i$ . This corresponds to a logistic cumulative distribution function, and can be shown graphically as an S-shaped curve known as an Item Characteristic Curve (ICC).

In this approach, the items in the scale have a similar ability to discriminate between respondents, i.e. the items discriminate equally. This characteristic distinguishes the Rasch model from any other IRT model. This characteristic is also referred to as parameter separability. This desirable property of specific objectivity defines a measurement scale, making the Rasch model especially attractive among IRT models because of its unique property. In other words, the comparison of two individuals is fully described by the difference in their deprivation level on the latent dimension. This is independent of which specific items were administered to them (item-independent person measurement). At the same time, item severity estimation is independent of

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<sup>5</sup>Since the model is specified in terms of the difference between  $\beta$  and  $\delta$ , only the distance between two parameters is meaningful. This means that in practice one is free to choose any reference point as the zero of the measurement scale and to express the units as it is most convenient.

the deprivation level of the sample on which it was calibrated (sample-free item calibration). This feature of specific objectivity is particularly relevant in the context of standard-based assessment, where the aim is to precisely estimate the level of an individual’s deprivation and identify which items are likely to be answered correctly at a given level of deprivation. Another appealing feature of the Rasch model is that the measures of individual severity (the estimated  $\beta$  parameters) are monotonically linked to the raw scores. For individual  $i$ , this is equal to  $y_i = \sum_{j=1}^J y_{ij}$ ,  $i = 1, \dots, N$ . Under the Rasch model, the observed raw score  $y_i$  is a sufficient statistic for the parameter  $\beta_i$  (Bartolucci et al., 2016). This implies that the raw score contains all the necessary information to represent the respondent’s level of deprivation on an ordinal scale. This means that individuals with the same score will have the same estimated deprivation level, regardless of their specific response pattern. Nevertheless, the price we have to pay for estimating a valid measurement scale is that the data have to fit the model and not vice versa. The Rasch model is a confirmatory model; only when the data meet its requirements can a satisfactory measurement tool be derived. Furthermore, the raw scores are only defensible on empirical grounds when the hypotheses are not rejected. The model assumptions are: (i) *conditional independence* of the responses, i.e. for each individual  $i$  the responses to the  $J$  items are statistically independent given the latent trait; (ii) *equal discrimination* or parameter separability. This property guarantees the specific objectivity of the measurement tool. Violation of equal discrimination implies that the ranking of the items in terms of severity may change depending on the respondent’s level of deprivation, which makes the “severity” construct somehow ambiguous (see Farcomeni et al. (2024) for more details), and finally (iii) *unidimensionality*. The main criticism is that the Rasch model is confirmatory, meaning that the empirical data must meet the model’s requirements. Therefore, testing the adherence of the data to the Rasch model assumptions is essential. Fit statistics provide a robust basis on which to assess the suitability of the model and the data for measurement purposes, particularly with regard to properties (i) and (ii). While unidimensionality remains a controversial issue in the literature, a careful analysis of the residual correlation matrix can help to assess property (iii).

Based on the Rasch approach, in order to obtain comparable estimates of deprivation rates for each ASEAN country, we have adopted the following strategy.

- (a) We used a Rasch model to construct a deprivation scale for the five selected countries, in order to create a valid ‘common scale’ against which country-specific scales could be calibrated. The deprivation thresholds were selected by considering these countries as a whole region.
- (b) In order to remove items that did not meet the Rasch assumptions and to obtain

country-specific item severities, we also estimated the Rasch model parameters also separately for each country.

- (c) We assessed whether there were differences in how the items functioned across countries (DIF). In other words, we checked whether individuals from different countries experiencing similar levels of deprivation were equally likely to respond positively to an item.
- (d) The thresholds used for classification were made comparable across countries by calibrating the measures obtained from the country-specific estimates against the ‘common scale’, while taking possible differential item functioning (DIF) into account.
- (e) We finally estimated the prevalence rates of deprivation across countries using these adjusted, country-specific thresholds.

Additional details on the model strategy can be found in sections 3.4 and 3.5.

## 3.2 Data description

Since the Asian Barometer Survey (ABS) was launched in 2001, five waves of the survey have been completed. The survey now covers 14 countries and regions in Asia: Taiwan, Hong Kong, mainland China, Japan, South Korea, Mongolia, the Philippines, Thailand, Singapore, Indonesia, Vietnam, Malaysia, Myanmar, and Cambodia. As a regional partner of the Global Barometer Surveys, the Asian Barometer Survey collects public opinion data on topics including political values, democracy, governance, human security, economic conditions through face-to-face interviews across Asia. The ABS is the first cross-national survey project led by East Asian scholars and the first survey project of its type in East Asia. A typical Asian Barometer survey involves around 1,200 respondents per country, allowing for a minimum confidence interval of plus or minus 3 per cent at a 95 per cent probability level. Samples may be stratified or weighted to ensure adequate coverage of rural areas and minority populations. Consequently, the samples selected for Asian Barometer surveys accurately represent the entire adult, voting-age population of each surveyed country.

The interviews are based on a stratified random sample of eligible voters. They are conducted using standardized research protocols and survey instruments. This generates a region-wide base of scientifically reliable and comparable data. A standard questionnaire includes a core set of questions, while additional questions are more specific to the country under study. Our focus is on the economic conditions of families, specifically household ownership of durable goods and access to services. The Asian Barometer dataset is primarily composed of categorical and count data. This is because the surveys often ask questions that result in categorized responses. Specifically,

poverty is often assessed using subjective indicators, such as asking individuals to self-report their perceptions of poverty or evaluating their ability to afford certain goods and services. Both methods result in categorical data. Deprivation indicators, which focus on whether individuals can afford basic necessities, also yield categorical data. Indicators of material deprivation should align with each country’s specific socio-economic context and development priorities. However, there is no single, official list of indicators for measuring material deprivation specifically for ASEAN countries. This analysis adopts one possible approach: selecting a set based on the European Union’s official list of deprivation items that is compatible with the available ABS data. For this analysis, we used the data from the fifth wave survey for all the selected countries.<sup>6</sup> The fifth wave survey period spanned from 2018 to 2021, though most interviews were conducted in 2019. Data from various countries was released at different times within this period. Some data became available as late as September 2022 and April 2023.

### **3.3 Selection of the material deprivation items**

In this section, we present our selection of indicators derived from ABS data to identify households experiencing material deprivation. In the absence of an official scale, we based our selection primarily on the items included in the official EU scale. However, we also considered the recommendations of Mahadevan and Hoang (2016). For their analysis of the relationship between income poverty and multidimensional deprivation in Vietnam, they chose a set of indicators from the 2010 Vietnam Household Living Standards Survey (VHLSS). Due to unavailable data, we had to omit some items from the EU deprivation scale (e.g., having arrears or being able to afford an annual vacation away from home) and from Mahadevan and Hoang’s list. The list of items selected for this analysis, along with the estimated percentage of the population that cannot cope with or do not possess each item, is presented in Table 1.

It is clear that other indicators could have been chosen, and more work is needed to refine this list. Considering the limitations of the available data from the Asian Barometer Survey, this list is the best synthesis possible. A technical issue that remains unresolved concerns the unidimensionality of the list, a requirement of the Rasch model, and it will be addressed in the following section.

### **3.4 Model estimates and diagnostics**

Rasch measurement is a rigorous method of converting an ordinal scale into an interval scale. This allows for a more precise interpretation of scores and enables arithmetic operations, such as calculating averages. Additionally, deprivation estimates are person-

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<sup>6</sup>The sixth wave survey is currently in progress or still being prepared for some countries.

Table 1: List of items included in the deprivation scale, and relative frequency of affirmative responses in the population

Item Label	Definition in the ABS questionnaire	Item equal to 1	% of 1
NoBasicNeeds	Does the total income of your household allow you to satisfactorily cover your needs?	Does not	28.89
NoRefrigerator	Do you or your family own a refrigerator?	Does not possess	38.35
NoElectricFan	Do you or your family own an electric fan or an air conditioner?	Does not possess	30.99
NoMobilephone	Can you afford a mobile phone?	Cannot afford	12.47
NoAccessInternet	How easy or difficult is to obtain access to the internet?	Difficult/ Very difficult	30.75
NoCar	Do you or your family own a car/jeep/van?	Does not possess	74.92
NoMotorbike	Do you or your family own a scooter/motorcycle?	Does not possess	19.40
BadRoad	In what condition is the road leading to interviewee's residence?	Unpaved	49.15
NoSewage	Is there a sewerage system in the house?	No	53.18
NoElectricity	Is electricity the main source of lighting in the house?	No	11.36
NoTapWater	Is tap water as the main source of drinking water in the household?	It is not	49.29

and item-independent because the measure satisfies the properties of the Rasch model. However, an ordinal score can only be transformed into an interval-level variable when the data from a questionnaire aligns with the model's expectations. Therefore, a rigorous evaluation must first be conducted to determine whether the data satisfactorily aligns with the Rasch assumptions. In this analysis the Rasch model is estimated using pooled data from the five ASEAN countries and the previously selected eleven-item scale. The parameters are estimated using the conditional maximum likelihood (CML) method, and the estimations include sampling weights. Rasch model-based assessment of data adherence utilizes item statistics, specifically item *Infit* and *Outfit* statistics (Wright and Masters, 1990). These statistics are derived from Rasch residuals and are used to compare observed response patterns with the expected patterns under the 'truth' of the measurement model. If the data are consistent with the assumptions of the Rasch model, the expected value of these statistics is one. Infit values between 0.7 and 1.3 generally meet the model assumptions to an acceptable degree. Values greater than 1.5 suggest that the item should not be used for scoring because it may introduce significant bias into the measurement. Similar standards can be applied to item outfit statistics, though they are more sensitive to unexpected observations. Outfit statistics with values above the 2 threshold help identify items with idiosyncratic meanings for a small group of respondents. This reveals problems with how that group interprets the question differently. Values below the threshold of 1 indicate overfitting of the data to the model. In other words, the observations are too predictable, and

therefore, unrealistic, due to their deterministic nature. Rather, a zone of uncertainty around the item-level severity (and the person’s level of deprivation) is intrinsic to the probabilistic nature of Rasch-type models. The results demonstrate a high degree of consistency between the data and the Rasch model (see the third and fourth columns of Table 2). The Infit statistics fall within the interval (0.7, 1.3), and the Outfit statistics are consistently below 2. This indicates that the selected items contribute equally to a valid measure of deprivation. The information power of the measurement scale is assessed using the Rasch reliability statistic, which is defined as the proportion of total variation in the population accounted for by the measurement model. Values exceeding 0.75 are indicative of satisfactory performance of the measure. The estimated Rasch reliability index is 0.79, confirming that the 11-item scale effectively differentiates respondents based on their level of deprivation. Furthermore, a two-parameter logistic item response theory (IRT) model was used to estimate the discriminating power of each item (Bartolucci et al., 2016). Items with low discrimination levels were excluded from the potential list a priori. Item severity parameters, along with their standard errors, are reported in Table 2. Respondent severity parameters estimated for each raw score are reported in Table 3. The standard deviation of the item severity param-

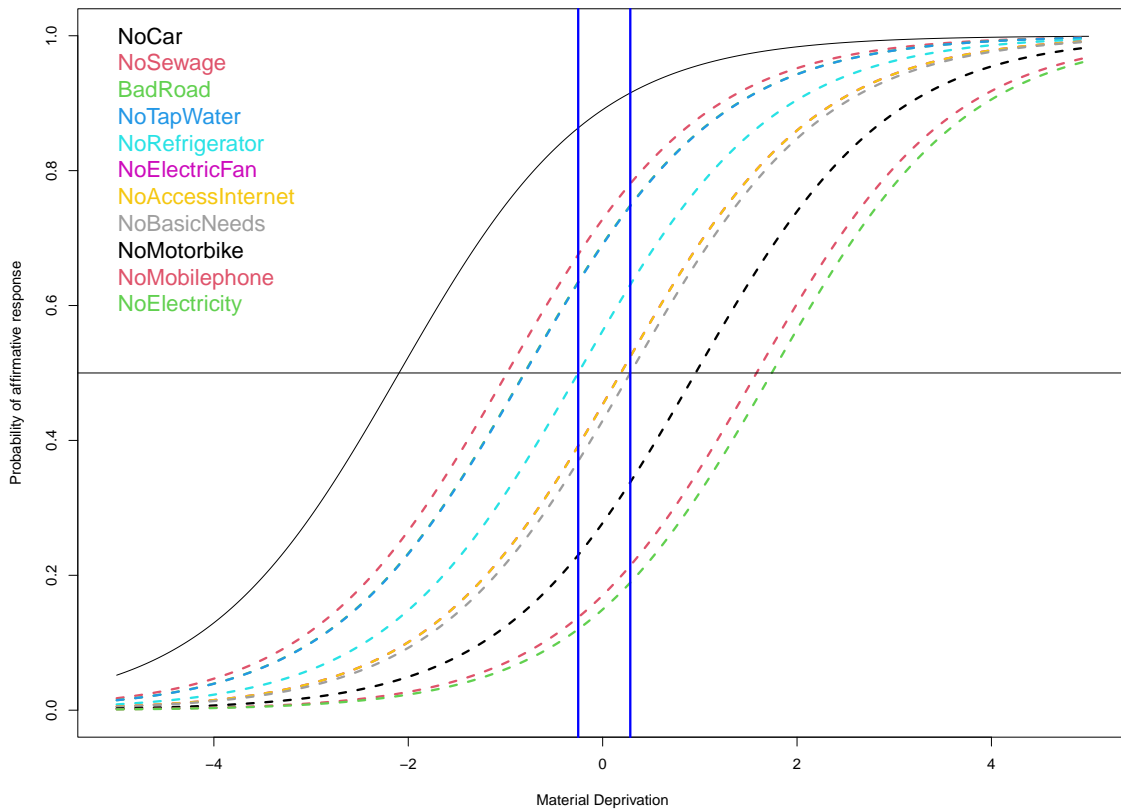
Table 2: Item severity parameter estimates, standard errors, infit and outfit statistics. Items are listed in order of estimated severity

Item	Severity	S.E.	Infit	Outfit
NoCar	-2.095	0.032	1.008	0.906
NoSewage	-0.985	0.030	1.010	0.997
BadRoad	-0.806	0.030	0.978	0.933
NoTapWater	-0.801	0.030	1.015	0.959
NoRefrigerator	-0.252	0.031	0.699	0.571
NoElectricFan	0.187	0.032	0.779	0.624
NoAccessInternet	0.188	0.032	1.297	1.575
NoBasicNeeds	0.284	0.033	1.162	1.100
NoMotorbike	0.956	0.037	1.170	1.840
NoMobilephone	1.583	0.043	1.107	1.049
NoElectricity	1.740	0.045	0.796	0.604

eters is 1.15, which suggests that the items cover a reasonable range of severity. This means that the items cover quite extreme situations, such as ‘very high’ or ‘very low’ deprivation condition. The location of the items on the deprivation continuum allows for a hierarchy of severity. The least severe experience is NoCar. Even people with a low level of deprivation may have difficulty owning a car. The next item is NoSewage, which refers to whether the respondent has access to a proper sewage system inside the house. The most severe experience is NoElectricity (i.e., not having electricity

as the main source of lighting in the house), which is estimated to be an extremely poor condition. The Item Characteristic Curves in Figure 1 show the probability of an affirmative response against respondent severity. The items are ordered based on their severity.

Figure 1: Item Characteristics curves (ICC) for the selected items. The blue vertical lines represent the selected thresholds to estimate deprivation and and extreme deprivation.



As mentioned in the previous section, it is necessary to determine if all the items on the list measure one single latent trait. Unidimensionality is assessed by calculating the residual correlation matrix of each pair of items. According to Lord et al. (1968), the items should only be correlated through the latent trait that the test is measuring. If significant correlations remain among the items after the latent trait's contribution is removed, i.e., among the residuals, then the items are locally dependent, or a subsidiary dimension of the measurement is present that is not accounted for by the main Rasch dimension. Any residual correlation exceeding a reasonable threshold violates the model assumption of conditional independence. Confirmatory factor analysis of the residuals is also used to investigate the existence of a possible second latent trait. The underlying hypothesis is that there is only one dimension when the residuals do not contain other significant dimensions, i.e., when they do not show any latent residual

trait. In practice, unidimensionality is assumed if the percentage of explained residual variance is not substantial (less than 50%-60%). Principal component analysis of the residual correlation matrix revealed the presence of only one main dimension. The absolute value of all pairwise residual correlations was reasonable small, confirming the hypothesis that all correlations among items result from their common association with a single latent trait. Overall, the Asian Barometer data demonstrate a satisfactory fit to the Rasch model when considering the five countries as a whole. This ensures that the 11-item scale is based on a well-founded construct and can be used as a common reference scale against which country-specific scales can be calibrated.<sup>7</sup>

As mentioned earlier, respondent and item parameters are measured on the same scale. This means that a person's level of deprivation and an item's severity are measured using the same unit on the same scale. The respondent severity parameters estimated for each raw score are reported in Table 3. Estimating prevalence rates requires identifying thresholds that distinguish the non-deprived from the deprived and, possibly, those who are moderately deprived from those who are extremely deprived. Based on the location of the items on the latent trait, a range of thresholds can be established that correspond to varying degrees of material deprivation, from mild to extreme. In this study, two thresholds were selected: the first to identify deprivation and the second to identify extreme deprivation. The first threshold is set according to the severity parameter of `NoRefrigerator`, which is around the middle of the ICCs and equal to -0.25. Materially deprived individuals are those whose estimated level of deprivation is above this threshold. This corresponds roughly to individuals whose raw score is at least equal to five (see Table 3). They account for 32.4% of the total population of ASEAN countries. The second threshold is set according to the severity of item `NoBasicNeeds`, the eighth most severe item, which equals 0.28 on the common ASEAN scale. Those classified as extremely deprived are highly likely to have an estimated level of deprivation above 0.28. This group corresponds to individuals with a raw score greater than seven (see Table 3) and comprises 21.7% of the total population.

Following a probabilistic approach, prevalence rates are estimated based on these selected thresholds, and individuals are assigned to a normal distribution of deprivation along the latent trait, depending on their own raw score. This distribution is centered on the severity parameter of each individual corresponding to their raw score, and the scale is equal to the standard error of that parameter. Therefore, the probability of being deprived or extremely deprived is simply the probability of being above the fixed thresholds. The corresponding prevalence rates are the sample-weighted sum of these

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<sup>7</sup>To give the scale robustness, we also conducted a similar exercise considering the median values of the item severities estimated separately for each country. We then compared the set of item severities for each country to these median values. The results did not change significantly.

Table 3: Item severity parameter estimates, standard errors, infit and outfit statistics. Items are listed in order of estimated severity

Raw Score	Severity	S.E.
0	-3.562	1.490
1	-2.769	1.108
2	-1.851	0.849
3	-1.205	0.746
4	-0.704	0.700
5	-0.257	0.680
6	0.244	0.681
7	0.691	0.700
8	1.227	0.748
9	1.863	0.847
10	2.628	1.051
11	3.544	1.490

probabilities. To obtain the corresponding threshold in terms of a raw score, we examined the estimated severity of individuals ( $\beta$ s parameters in Table 3) corresponding to each raw score. The value closest to the deprivation threshold (-0.25) approximates the severity of individuals with five affirmative items, while the value closest to the extremely deprivation threshold (0.28) approximates the severity of a raw score of seven. These two raw score values represent the cut-off of the counting approach to be used for comparison with the probabilistic latent approach.

### 3.5 How similar is deprivation perceived across ASEAN countries?

When comparing deprivation rates across Southeast Asian countries, it is important to note that the order of item severity on the ASEAN common scale is not fixed across the five selected countries. The relative severity attributed to each of the eleven items may vary across ASEAN since deprivation conditions are experienced and managed differently in different cultures and livelihood systems. Additionally, nuances in translation can result in the same question being interpreted differently in different contexts. The position of the items on the severity scale is not imposed *a priori*, but rather determined by analyzing the specific data collected.

Differential Item Functioning (DIF) analysis is a key step in assessing the scale's performance in terms of comparability. DIF occurs when individuals with the same latent trait respond differently to certain items due to their different life circumstances. Moreover, in the presence of DIF, the counting approach would lead to substantially biased results for this country compared to others, as the raw scores would reflect dif-

ferent levels of severity of the latent trait. This suggests that the same score would correspond to a different level of deprivation in another country (see Farcomeni et al., 2024, for further discussion). We assess differential item functioning (DIF) using the delta plot method (Angoff and Ford, 1973). This method is straightforward, computationally inexpensive, and produces an appealing graphical output: the diagonal plot. This score-based method compares the proportions of affirmative responses in the “focal” and “reference” groups. In this method, each country is considered a focal group and is tested for DIF against the remaining countries, which represent the reference group. In the delta plot method, the proportions of affirmative responses are transformed into normalized scores. In the absence of DIF, pairs of delta scores (one for each item) lie within a narrow ellipse along the diagonal of the plot. If there are items with DIF, the delta plot will clearly depart from this ellipse, making the items with DIF easily visible. Items are flagged as DIF or non-DIF depending on the size of their perpendicular distance from the diagonal.<sup>8</sup> Table 4 shows how many items were excluded from the anchoring procedure due to different item functioning. All the items in Vietnam can be considered common to the global ASEAN scale, ten items in Malaysia, nine items in Indonesia and eight items in Malaysia and Thailand. When differential item functioning (DIF) exists for only a few items, as in our analysis, the remaining items can be used as anchors to calibrate the measurement in a comparable manner across countries.

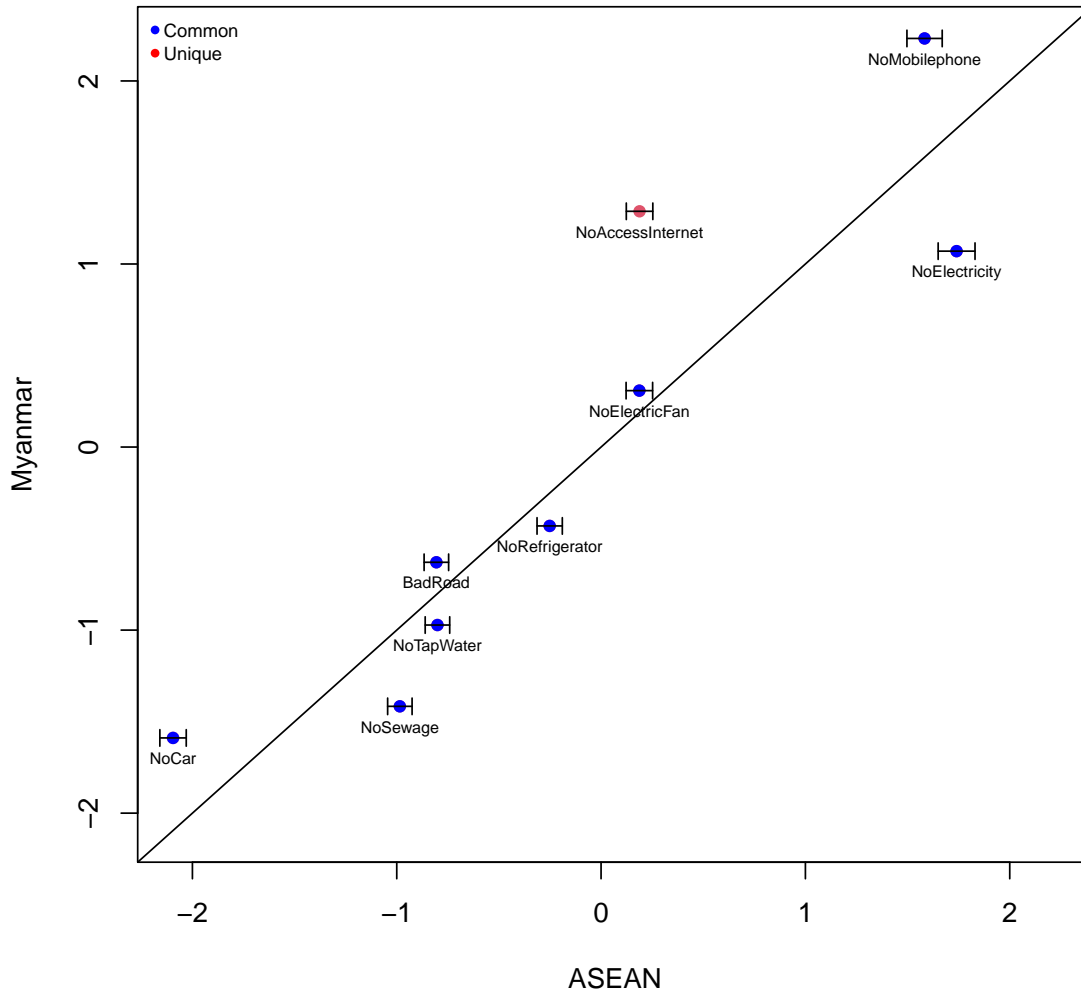
Table 4: Number of differential functioning items detected in the five ASEAN countries

Number of unique items	Country
0	Vietnam
1	Myanmar
2	Indonesia
3	Malaysia, Thailand

Figure 2 shows the different behavior of the unique item `NoAccessInternet` in Myanmar, by plotting its item severities against those of the ASEAN region. Figure 3 instead illustrates the distinct behavior of the unique items `NoAccessInternet`, `NoTapWater`, and `NoCar` in Malaysia. These items are flagged in red in the graph.

<sup>8</sup>Following Magis and Facon (2012) the flagging criterion is designed to automatically adjust the minimum distance to the data.

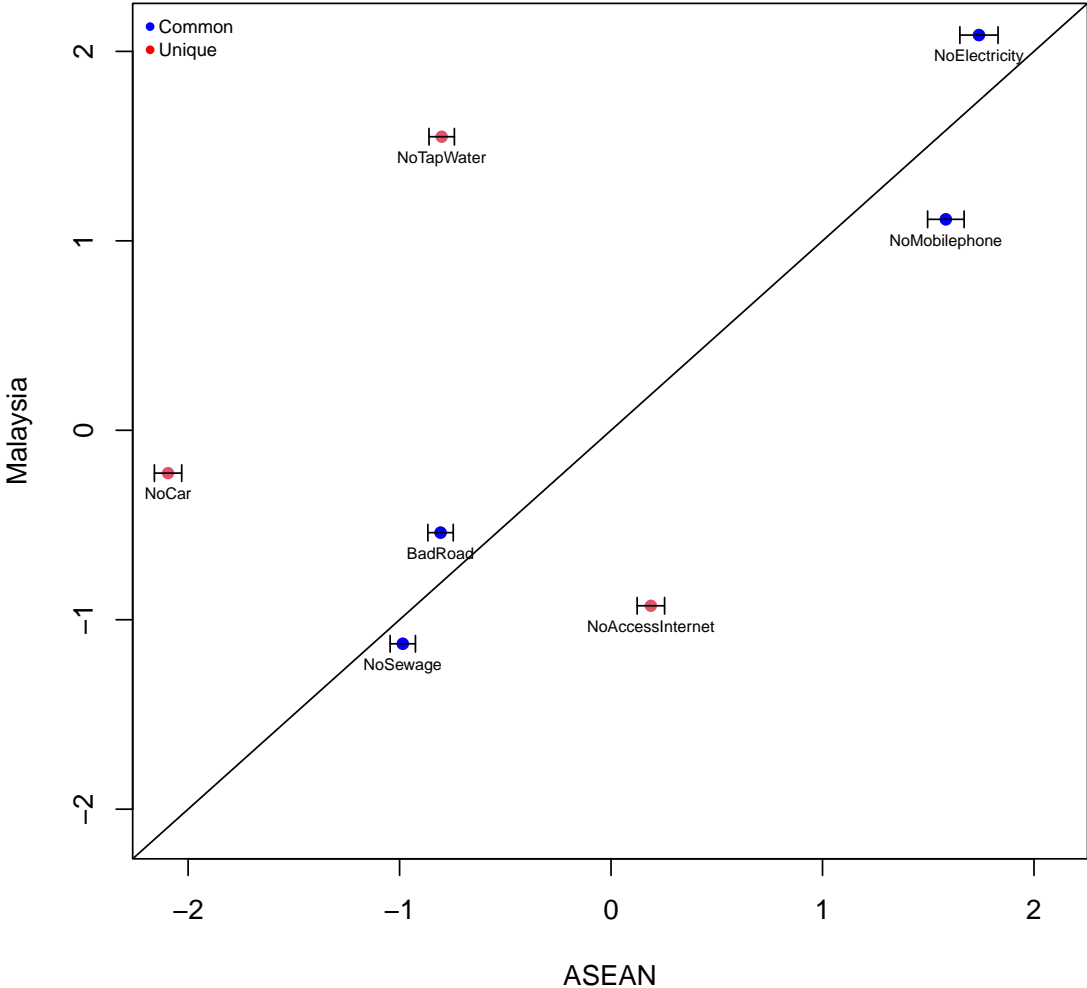
Figure 2: Delta Plot for Myanmar: Items flagged in red are identified as differential item functioning (DIF)



As shown in Figure 2 the severity of the item **NoAccessInternet** in Myanmar does not lie on the diagonal, and it is higher than in the entire ASEAN region. Compared to other aspects of deprivation, it seems that residents in Myanmar have relatively easy access to the web. Although 33% of the population does not have internet access, this percentage is much lower than expected. This item exhibits ‘unique’ behavior.

As shown in Figure 2, the severity of the item **NoAccessInternet** in Malaysia is instead higher than in the entire ASEAN region. In fact, over 27% of the population lacks internet access, one of the highest rates of deprivation in Malaysia. Although each item is designed to represent the same experience of deprivation, the severity of each item may differ by more than the specified tolerance in a given country. This is

Figure 3: Delta Plot for Malaysia: Items flagged in red are identified as differential item functioning (DIF)



due to the different conditions experienced by respondents in the two cultures. When this occurs, only items with a “common” behavior will be used to estimate the country-specific thresholds.

## 4 Deprivation rates across ASEAN countries

### 4.1 Estimation of country-specific thresholds

When measuring deprivation on a regional scale, the estimated prevalence rates must be comparable across countries within the region. To achieve this, the thresholds used to classify deprivation should be defined on a reference scale, allowing for the estimation of prevalence rates using an equivalent metric. We define this common metric by mapping the ASEAN global scale thresholds onto the national ones. The calibration procedure uses a linear transformation to equate the means and standard deviations of the severities of common items. The equating procedure begins by selecting a set of anchoring items that demonstrate common functioning between the focal country and the reference group (the ASEAN region). These items are then used as anchoring points for the metric. In summary, country-specific adjusted thresholds,  $th_{adj,c}$ , are defined as follows:

$$th_{adj,c} = \hat{\mu}_{c,itcom} + (th - \hat{\mu}_{ASEAN,itcom}) \times \frac{\hat{\sigma}_{c,itcom}}{\hat{\sigma}_{ASEAN,itcom}}, \quad (3)$$

where  $\hat{\mu}_{c,itcom}$  and  $\hat{\mu}_{ASEAN,itcom}$  are the means of country  $c$  and of ASEAN region evaluated on the common items;  $\hat{\sigma}_{c,itcom}$  and  $\hat{\sigma}_{ASEAN,itcom}$  are the standard deviations of the common item severity parameters in country  $c$  and in the ASEAN scale. This calibration ensures that all of the individual parameter estimates in different contexts are expressed using the same unit of measurement. Each individual is assigned a normal distribution centered at their corresponding raw score severity parameter, with a standard deviation equal to the standard error of that parameter. The probability of being deprived is then computed as the cumulative probability of being beyond the country-adjusted threshold.

Table 5 reports the deprivation rates of the five ASEAN countries estimated with the probabilistic and counting approaches, along with the corresponding margins of error ( $\pm$ MoE).

Table 5: Prevalence rate of deprivation using the 11-item Rasch measurement scale and using the counting (cut-off equal to 5)

Country	Code	Probabilistic	MoE	Counting	MoE
Thailand	THA	13.30	1.90	12.80	1.90
Indonesia	IND	39.40	2.40	42.70	2.50
Vietnam	VTN	16.60	2.10	11.10	1.80
Malaysia	MLY	10.90	1.70	0.60	0.40
Myanmar	MTN	73.80	2.10	69.60	2.20

The prevalence rates of extreme deprivation for the five ASEAN countries countries are reported in Table 6.

Table 6: Prevalence rate of deprivation using the 11-item Rasch measurement scale and using the counting (cut-off equal to 7)

Country	Code	Probabilistic	MoE	Counting	MoE
Thailand	THA	4.10	1.10	1.80	0.80
Indonesia	IND	18.90	2.00	14.90	1.80
Vietnam	VTN	6.70	1.40	2.70	0.90
Malaysia	MLY	3.40	1.00	0.00	0.00
Myanmar	MTN	59.00	2.40	36.80	2.30

## 4.2 Understanding individual deprivation trait

In the latent approach, an individual’s estimated level of deprivation is conceptualized as a continuous variable. This implies that the variable can theoretically assume any value along a continuum and can be comparatively analyzed in a standardized and meaningful manner. Understanding the latent trait is essential for analyzing possible relationships with individual characteristics and leads to more informed decision-making. By exploring the potential of this method, we aim to identify the most influential factors contributing to material deprivation. These factors are indispensable prerequisites for effective policies aimed at reducing deprivation. In particular, we identify individual predictors of deprivation while taking a contextual perspective into account. Due to the hierarchical structure of the data, in which individuals are nested within countries, we estimate a multilevel model that incorporates both micro- and macro-level predictors of deprivation within a single explanatory model. When deprivation is treated as a continuous variable, this is a novel and reasonable tool for analyzing the determinants of deprivation and, where data are available, deprivation profiles. Having contextual variables available at the national and regional levels could in fact help tremendously with evaluating the impact of community- and individual-specific shocks on shaping deprivation traits (see also Günther and Harttgen, 2009). Introducing poverty rate is a valid approach for understanding variability across ASEAN countries because it reveals disparities in living standards and progress toward economic well-being. Macro data come from the World Bank’s PIP (Poverty and Inequality Platform). The first level of our main two-level random intercept log-linear model states:

$$\begin{aligned} \log(\text{Deprivation}) = & \alpha_{s[i]} + \beta_{1([i])} \log(\text{hh income})_i + \beta_{2([i])} (\text{Size of the hh})_i + \\ & + \dots + \beta_{10([i])} (\text{UrbanArea} * \text{Size of the hh})_i + \epsilon_i \end{aligned} \quad (4)$$

where  $s[i]$  is the country corresponding to household  $i$ ,  $i = 1, \dots, 6804$ .

The main feature of the higher level models for the parameters in equation (4) is that every group of state level parameters is normally distributed around a national mean. We therefore allow  $\alpha_s$  to vary across ASEAN countries, modeling as a function of contextual predictors (in this case the country poverty rate), to capture cross-sectional contextual effects:

$$\alpha_s \sim N(\alpha + \delta_1 \mathbf{Z}_{1,s}, \sigma_\alpha^2), \quad (5)$$

where  $\mathbf{Z}_1$  denote the matrix of country level of poverty that affect the country intercepts,  $\alpha_s$ , for  $s = 1, \dots, 5$ . The estimation of the model is reported in Table 7 and Table 8.

Table 7: Estimated coefficients with relative standard errors of individual characteristics in the fitted varying-intercept and varying-slope multilevel regression model in the ASEAN countries.

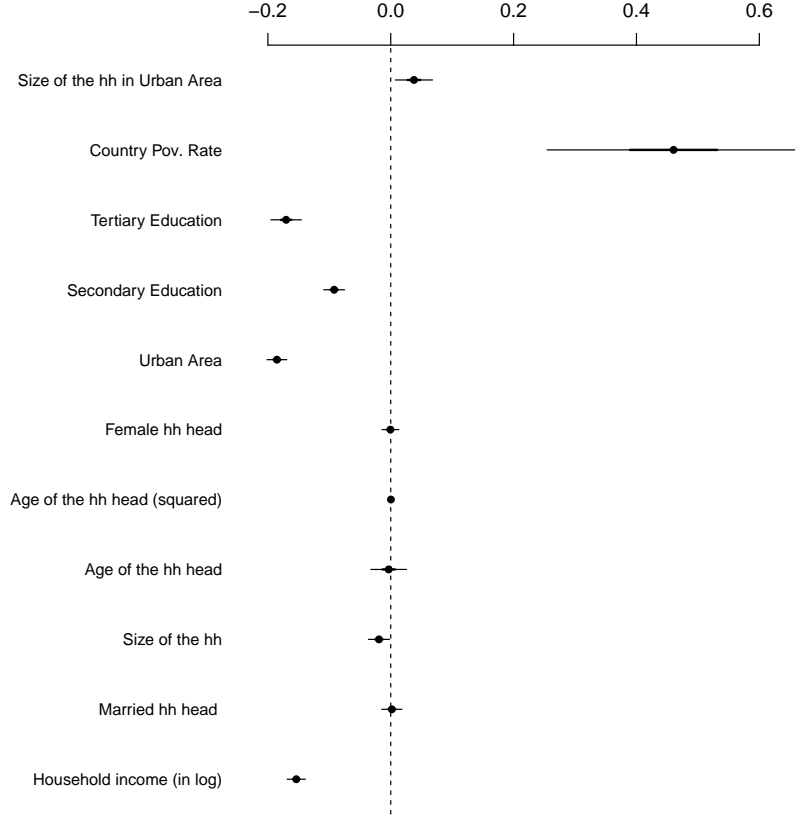
	Estimate	Std. Error
Intercept	1.82	0.05
Household income (in log)	-0.15	0.01
Married hh head	0.00	0.01
Size of the hh	-0.02	0.01
Age of the hh head	-0.00	0.01
Age of the hh head (squared)	0.00	0.00
Female hh head	-0.00	0.01
Urban Area	-0.18	0.01
Secondary Education	-0.09	0.01
Tertiary Education	-0.17	0.01
Country Pov. Rate	0.46	0.10
Size of the hh in Urban Area	0.04	0.01

Table 8: Estimated random coefficients for ASEAN countries.

	Intercept
Thailand	0.02
Indonesia	-0.11
Vietnam	-0.09
Malaysia	0.05
Myanmar	0.13

Estimated coefficients of the individual and country predictors are shown in Figure 4. Thinner lines represent the  $\pm 2$  standard errors of each estimated parameter, while thicker lines correspond to the  $\pm 1$  standard errors. The coefficients have the expected signs and reasonably small standard errors. As expected, the relationship between household income and deprivation is negative. The estimated elasticity coefficient is equal to  $-0.15$ , meaning an increase of 10 percent in household income translates to a 15 percent decrease in the deprivation scale. All countries exhibit high returns to schooling. Secondary education is associated with a 10 percent reduction in deprivation, while a bachelor's degree is associated with a 16 percent reduction. After controlling for individual characteristics and country of residence, a significant urban-rural disparity remains. People living in rural areas experience higher levels of deprivation than those living in urban regions. However, urban households with children and those of larger sizes experience higher levels of deprivation. As expected, there is a significant positive correlation between a country's poverty rate and its deprivation rate. Both indicators reflect a lack of resources and opportunity, though they measure different aspects of well-being.

Figure 4: Estimated coefficients of individual predictors, along with their standard errors



The estimated standard deviations at the individual and country levels, reported in Table 9, are  $\sigma_y = 0.288$  and  $\sigma_\alpha = 0.278$ , respectively. Introducing a country-level predictor (i.e., the country poverty rate) reduced the unexplained variation between counties to  $\sigma_\alpha = 0.115$ . This predictor left the within-country variation unchanged, which makes sense since it is a country-level predictor that cannot explain variation within countries. The resulting Intraclass Correlation Coefficient (ICC), equal to equal to  $\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_y^2} = 0.140$ , indicates that a substantial proportion of the total variation is attributable to country differences, especially considering that we have only five countries.

Table 9: Estimated standard deviations, without and with country-level predictors

	Group	St. Dev.	Variance
1	country	0.272	0.074
2	Residual	0.288	0.080
1	country	0.115	0.013
2	Residual	0.288	0.080

## 5 Concluding remarks

Using the latest wave of the Asian Barometer survey, we propose a novel method for estimating the level of deprivation at the individual level as a latent, unobservable, continuous trait in five ASEAN countries. We consider deprivation to be a forward-looking indicator of a decline in welfare. Thus, we have selected a set of eleven observable items representing individual-level deprivation indicators. The items in question form a scale that measures individual economic deprivation on a continuous metric. Comparable prevalence rates of moderate and severe deprivation have been estimated across ASEAN countries. National-level figures were calculated by incorporating sampling weights. To ensure an adequate level of cross-country comparability, we estimated deprivation rates using country-specific thresholds. We obtained these thresholds by calibrating the severity of each of the eleven items across the entire ASEAN region. First, we estimated a "global" scale. Then, we used a calibration procedure to estimate the country-specific thresholds. Calibration of the scale is achieved by equating the mean and standard deviation of the severity parameters of items that are common to the national and reference scales. These items serve as anchoring points for the metric. We identified different behavior (DIF) in only a limited number of items and only in some countries. In such cases, only items with similar severity levels were used for anchoring.

The Asian Barometer Survey, designed as a combined household and attitudinal survey, provided an interesting case for selecting and validating deprivation indicators. Moreover, the use of potential high-frequency comparable surveys, such as the ABS, can provide timely useful information on the evolution of population's welfare. However, due to its design, the ABS is limited in terms of questions on household socioeconomic characteristics. A detailed study of the questions to be included in a proper household survey to capture the 'experience' of deprivation as perceived by individuals would enhance the methodology proposed in this study. Finally, since deprivation as a latent trait can be treated as a continuous variable, we modeled the level of deprivation for each individual as a function of their characteristics and contextual predictors. This enabled us to identify the primary factors influencing deprivation risk among different groups. Furthermore, identifying factors at the country level will result in national policies that manage the risk of economy-wide shocks, as well as effective mechanisms that reduce the risk faced by impoverished individuals.

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