Transitions in Deprivations and Poverty

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This paper explores a novel way to analyse poverty dynamics, specific to certain measures of multidimensional poverty, like the 'adjusted headcount ratio' of Alkire and Foster (2011a). Assuming panel data, I show that a simultaneous and comprehensive account to transitions in deprivations and poverty allows to handle complex interdependencies between dimensions in a dynamic context and, moreover, permits several advanced types of analyses. These analyses include (i) a decomposition of changes in multidimensional poverty, which reveals *why* poverty decreased or increased; (ii) a framework to examine and understand the relation of the dashboard approach and dimensional contributions to multidimensional poverty in a dynamic setting; (iii) analyses which illuminate the process of the accumulation of deprivations. The suggested types of analyses are illustrated using German panel data. Implications for monitoring, policy evaluation, and strategies for analyses with repeated cross-sectional data are discussed.

Keywords: multidimensional poverty; poverty dynamics, Alkire-Foster method, dimensional breakdown, dashboard approach, SOEP

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1 Introduction

The significance of panel data in the analysis of poverty has long been recognized. Indeed, panel data is essential for a thorough analysis of poverty dynamics. A prominent question in this line of research is how to distinguish and quantify chronic and transient poverty. By now, rather different methodological strategies have been devised and refined to study this and related questions. Frequently applied are the components-of-variance approach (Lillard and Willis, 1978), the spell approach (Bane and Ellwood, 1986), and other component-based methods (Jalan and Ravallion, 1998).[1] Applications cover developing and advanced economies alike and frequently employ several of the aforementioned techniques simultaneously (e.g., Stevens, 1999, Bigsten and Shimeles, 2008). In their seminal contribution, Bane and Ellwood (1986) motivate the application of hazard-type models, by pointing out that these models also allow to illuminate the driving factors behind poverty entries, exits, and reentries, i.e. the covariates of poverty transitions. Another emergent literature for which panel data is essential, aims to measure lifetime poverty (e.g., Bossert *et al.*, 2012). This literature accounts for the timing of poverty experiences, i.e. duration and sequencing of poverty spells are emphasized. Hoy and Zheng (2011), for instance, argue that poverty experiences early in the life cycle should be considered more severe.

Recently, substantive improvements in multidimensional poverty measurement have been achieved as well (Tsui, 2002, Bourguignon and Chakravarty, 2003, Alkire and Foster, 2011a). So far multidimensional poverty measures have mostly been applied to cross-sectional or repeated cross-sectional data (e.g, Alkire and Santos, 2014, Alkire *et al.*, 2014b, Alkire and Seth, 2015). First attempts however also exploit panel data. Alkire *et al.* (2014a), for instance, address chronicity within multidimensional poverty, whereas Alkire *et al.* (2015, p.273–276) suggest analyses by so-called dynamic subgroups, e.g., the ongoing poor, non-poor and those exiting or entering poverty. Finally, Apablaza and Yalonetzky (2013) use panel data to calculate entry and exit probabilities for multidimensional poverty measures and show that the adjusted headcount ratio, a member of the Alkire-Foster class of measures, and its partial indices can be related to transition probabilities in principle.

The present paper explores a novel way to better understand poverty dynamics, unique to certain measures of multidimensional poverty. As this approach requires the properties of dimensional breakdown and subgroup decomposability, I adopt the 'adjusted headcount ratio', M_0 suggested by Alkire and Foster (2011a) as measure for multidimensional

[1] See also e.g., Rodgers and Rodgers (1993), Jalan and Ravallion (2000), Hulme and Shepherd (2003), Mckay and Lawson (2003).

poverty, which additionally satisfies also other important axioms.[2] The idea is that multidimensional measures which satisfy dimensional breakdown offer an inherent way to explore the driving factors behind changes in poverty. Apablaza and Yalonetzky (2013) show that changes in M_0 can be decomposed into changes in the dimensional contributions of M_0. However, the identification of the 'driving dimensions' or 'on-the-ground changes' (Alkire *et al.*, 2015, p.269) is not trivial due to interdependencies with other dimensions. In fact, I show that their identification is feasible but requires panel data. Specifically, the dimensional contribution to M_0, the weighted censored headcount ratios, are in general not independent from changes in other dimensions, which may complicate the analysis substantially. Following, Apablaza and Yalonetzky (2013), I reduce changes in aggregate partial indices to transitions in deprivations and poverty. However, I adopt a more comprehensive account to transitions in deprivation and poverty, which allows to handle the complex interdependencies between dimensions and, moreover, permits other advanced forms of analysis. For instance, I show how behavioural transitions (which drive changes in poverty) and mechanical transitions (which are due to the interdependence) can be discriminated. This discrimination allows me to decompose changes in multidimensional poverty such that the driving factors are revealed. Thus certain multidimensional poverty measure can inherently provide insights into *why* poverty changed. As the previous analysis requires panel data, which many countries still lack, I also explore under what conditions repeated cross-sectional data may provide equivalent insights. Taken by itself, these insights are vital for both monitoring and policy evaluation.

Another important form of analysis applies the distinction of behavioural and mechanical transitions to scrutinise poverty entries and exits. Then deprivations which were in place before entering poverty can be identified, just as deprivations which remain after leaving poverty. By drawing the attention to the timing of deprivations, this analysis subjects the process of *how deprivations accumulate* to critical scrutiny. A further interesting descriptive analysis follows if transitions into and out of deprivations are differentiated by poverty status, which also illuminates the accumulation process of deprivations—albeit, with a slightly different emphasis. Specifically, it can be tested whether e.g. poor and not in dimension d deprived persons are more likely to enter this deprivation than non-poor (and non-d-deprived).

In addition to that, the same techniques can be applied to each single indicator, the raw or uncensored headcount ratio. Importantly, this step allows to relate dimensional changes in multidimensional poverty to changes in its raw indicators, which not only provides a

[2]Ordinality, for instance, facilitates empirical applications, see Alkire and Foster (2011a) for more details.

useful framework for an empirical analysis, but also offers a natural way to rationalize potentially inconclusive findings. A deeper understanding of these relations is important for two reasons. First, this is of immediate importance from a policy perspective, since fighting poverty involves numerous policy fields, such as health, education, labour, or agriculture. Consequently, different agencies and departments play a part in fighting poverty, each of which focussed upon its own subset of prime indicators. For one, a strongly indicator-specific perspective runs the risk of ignoring interaction of deprivations (Stiglitz *et al.*, 2009, p.206). Moreover, subject specialists may want to know, how changes in 'their' indicators relate to changes in multidimensional poverty. We may, for instance, observe a decreasing unemployment rate and are tempted to declare the latest labour market reform a success. However, without further analyses, it remains unclear whether the labour market reform reached (and benefited) the poor after all. An adequate decomposition of the uncensored headcount can answer this question.

Second, the suggested framework also complements the debate on how to treat the joint distribution of deprivations within poverty analysis. While there is consensus that poverty *is* multidimensional and that 'the joint distribution' is the interesting part of poverty analysis (Ferreira and Lugo, 2013), there is also a lively debate on how to best measure poverty and the exact role of 'the joint distribution' therein. While some prefer genuine multidimensional poverty measures (Alkire and Foster, 2011b), others prefer a 'credible set of multiple indices' (Ravallion, 2011), and yet others suggest to complement the dashboard with a separate analysis of the joint distribution (Ferreira and Lugo, 2013). Advocates of multidimensional measures (e.g., Alkire *et al.*, 2011) highlight that exploiting the joint distribution in the identification step offers unique insights into poverty (e.g., the actual identification of the poor, if compared with the simple dashboard approach). Instead, critics of multidimensional poverty measures question the value-added of dimensional decompositions (Ravallion, 2011).[3] In sum, it is central to document and understand eventual discrepancies for monitoring, policy evaluation, to assess the role of the 'joint distribution' in poverty measurement and analysis.

The remainder is structured as follows: Section 2 briefly introduces the counting approach to multidimensional poverty. While section 3 outlines the suggested account to transitions in deprivations and poverty, section 4 presents additional types of analyses. Section 5 provides an empirical illustration and section 6 offer some concluding remarks.

[3]Other arguments of this debate can be found in Alkire *et al.* (2011), Alkire and Foster (2011b), Ravallion (2011, 2012), Alkire and Robles (2016).

2 Counting Approaches to Multidimensional Poverty

This section introduces the dual cutoff counting approach to multidimensional poverty of Alkire and Foster (2011a), which includes union and intersection approach as special cases (Atkinson, 2003). The exposition is restricted to aspects used in the subsequent empirical analysis. Alkire *et al.* (2015) provide a more comprehensive discussion.

Identification and Aggregation. The matrix y contains the available data, is of size $N \times D$, and describes for each individual the achievement in each dimension deemed relevant. Specifically, $y_{id} \geq 0$ represents the achievement of individual $i = 1, \ldots, N$ in dimension $d = 1, \ldots, D$. The row vector z, with $z_d > 0$, describes the deprivation cutoffs, i.e., the achievements necessary for not being considered as deprived in the respective dimension. Using this information, we obtain the deprivation vector c by counting weighted individual deprivations, i.e., the column vector's elements are $c_i = \sum_{d=1}^{D} w_d \mathbb{1}(y_{id} < z_d)$, with $0 \leq w_d \leq 1$ and $\sum_{d=1}^{D} w_d = 1$. The key idea of Alkire and Foster (2011a) is to define the so-called identification function as $\rho_k(y_i, z) = \mathbb{1}(c_i \geq k)$ for $k \in [1, D]$. An individual is considered poor if its weighted deprivation count is larger than a critical threshold k, the poverty cutoff. A simple form of aggregation is the calculation of the headcount ratio, which is defined as $H = q/N$, where $q = \sum_{i=1}^{N} \mathbb{1}(c_i > k)$ is the number of the poor. Following Alkire and Foster (2011a) the average deprivation among the poor (the intensity) is defined as $A = \sum_{i=1}^{N} \underline{c}_i/(qD)$, with $\underline{c}_i = \mathbb{1}(c_i \geq k)c_i$. Finally, the adjusted headcount ratio is defined as $M_0 = \frac{1}{N} \sum_{i=1}^{N} \underline{c}_i = HA$, which is sensitive to both changes in incidence and breadth of poverty. In principle other members of the FGT class of measures (see Foster, Greer and Thorbecke, 1984) can be applied as well—their discussion is however beyond the scope of this paper.

Decompositions. The adjusted headcount M_0 and both its single components and its changes over time have been shown to be decomposable in numerous ways. Let $h_d = \frac{1}{N}\mathbb{1}(y_{id} \leq z_d)$ denote the proportion of individuals deprived in d, the so-called uncensored headcount ratio and let $\underline{h}_d = \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}(c_i \geq k \wedge y_{id} \leq z_d)$ be the dimension-specific censored headcount. First, since the adjusted headcount ratio fulfills dimensional breakdown (Alkire and Foster, 2011a, 2016), it can be expressed as a weighted average of dimensional contributions (post identification),i.e. $M_0 = \sum_{d=1}^{D} w_d \underline{h}_d$.[4] Second, as the adjusted headcount ratio also fulfills subgroup decomposability, it can be expressed as

[4]Note that the headcount ratio H does not allow a dimensional breakdown, unless the intersection approach is applied, since then because of $A = 1$, $H = M_0$.

an population-weighted sum of population-specific poverty. For $l = 1, \dots, L$ subgroups $M_0 = \sum_{l=1}^{L} \frac{N^l}{N} M_0^l$. Finally, applying both properties allows to unfold M_0 even further, i.e., $M_0 = \sum_{l=1}^{L} \frac{N^l}{N} \sum_{d=1}^{D} w_d \underline{h}_d^l$.

If data on more than one point of time is available, we also can calculate and decompose changes of aggregate measures. Importantly, changes in the adjusted headcount can be decomposed into changes in dimension-specific censored headcount ratios (Apablaza and Yalonetzky, 2013). Specifically, absolute changes, denoted as ΔM_0, and relative changes, denoted as δM_0, can be decomposed into

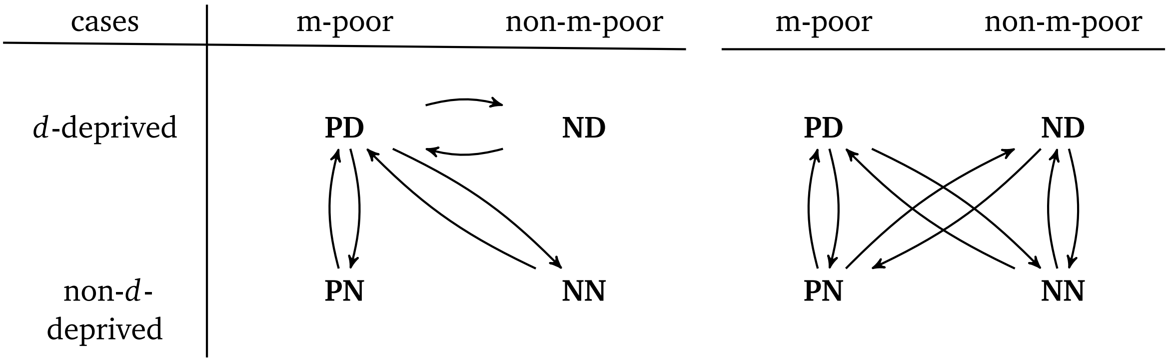
$$\Delta M_0^t = \sum_{d=1}^{D} w_d \Delta \underline{h}_d \quad \text{and} \quad \delta M_0^t = \sum_{d=1}^{D} s_d^{t-1} \delta \underline{h}_d, \tag{1}$$

where $s_d^{t-1} = \frac{w_d A_d(y^{t-1};z)}{A(y^{t-1};z)}$ is the contribution of dimension d to the average intensity. Alternatively, ΔM_0 can also be decomposed into population-specific changes (Alkire *et al.*, 2015, p.271-273) or dimensional changes by subgroups. If, moreover, panel data is available, Alkire *et al.* (2015, p.273-276) suggest to partition the population into dynamic subgroups. Subgroup decomposability then allows to state M_0 in each t as a population-weighted sum of these dynamic subgroups. Taking the difference over time reveals the change in M_0 to be the subpopulation-weighted sum the changes for the ongoing poor, the increase due to entries and decrease due to exits. Dimensional decompositions of dynamic subgroups can be analysed subsequently. The present paper argues that this analysis of dynamic subgroups is only one possibility how to exploit observability of transitions in deprivation and poverty offered by panel data. Together dimensional breakdown and subgroup decomposability allow a highly detailed and powerful analysis of poverty dynamics, via a joint analysis of transitions of deprivation and poverty.

3 Transitions in Deprivations and Poverty

Notation. In order to better understand changes in multidimensional poverty several different states have to be distinguished, depending on both poverty and deprivation status of an individual. Specifically, an individual is either poor and deprived in d (PD), not poor but deprived in d (ND), poor but not deprived in d (PN), or is neither poor nor deprived in d (NN). For any dimension d, figure 1 distinguishes these states along with those transitions (represented by arrows), that are relevant for changes in the censored headcount ratio (panel a) and the uncensored headcount ratio (panel b). For instance the censored headcount decreases if poor people leave the deprivation but remain poor ($PD \rightarrow PN$), leave the deprivation and poverty ($PD \rightarrow NN$) or leave poverty but not deprivation d ($PD \rightarrow ND$).

Figure 1: Transitions affecting censored and uncensored headcount ratios



(a) censored headcount ratio **(b) uncensored headcount ratio**

More formally, we can write these states for an individual i, the dimension d, and time t as $PD^t_{id} := c^t_i \geq k \wedge y^t_{id} < z_d$, $ND^t_{id} := c^t_i < k \wedge y^t_{id} < z_d$, $PN^t_{id} := c^t_i \geq k \wedge y^t_{id} > z_d$, and $NN^t_{id} := c^t_i < k \wedge y^t_{id} > z_d$. Moreover, we can denote the respective proportions in the population as follows: the censored headcount $\underline{h}_d$ is the share of the poor and deprived, whereas $h_d - \underline{h}_d$ are d-deprived but not poor, and $H - \underline{h}_d$ are poor, but not d-deprived. Finally, $1-H-h_d+\underline{h}_d$ are neither poor nor d-deprived. The transitions we may observe in the data can also be expressed using conditional probabilities. Specifically, the transitions from, say, $PD \rightarrow PN$, can be written as the product of the respective conditional probability and the share of the PD in $t-1$, i.e. $P(PN^t_d | PD^{t-1}_d) \times \underline{h}^{t-1}_d$. For notational convenience, I hereafter omit time and dimension index within the conditional probabilities. Figure 1 substantially facilitates subsequent analysis and argumentation, since it helps organize the different types of transitions relevant for the respective objective. For instance, transitions may be grouped according to inflow or outflow of poverty, or deprivation.

Behavioural and Mechanical Changes. Alkire *et al.* (2015, p.269–271) point out that changes in the censored headcount of a deprivation d may result from poor people leaving this deprivation, but also from leaving poverty due to developments in other dimensions.[5] The present account to transitions in poverty and deprivations allows to formulate these

[5]Note that censored headcount ratios are independent of achievements in other dimensions, once identification is accomplished (Alkire and Foster, 2016, p.10–11). However, poverty status may change over time and censored headcounts are sensitive to these changes through identification.

interdependencies among dimensions more precisely. Specifically, the law of total probability allows us to write the difference in the censored headcount ratios using all possible transitions which partition the probability space as follows:[6]

$$\begin{aligned}\Delta\underline{h}_d = & -P(ND|PD)\times \underline{h}_d^{t-1} + P(PD|ND)\times(h_d^{t-1}-\underline{h}_d^{t-1})\\ & -P(PN|PD)\times \underline{h}_d^{t-1} + P(PD|PN)\times(H^{t-1}-\underline{h}_d^{t-1})\\ & -P(NN|PD)\times \underline{h}_d^{t-1} + P(PD|NN)\times(1-H^{t-1}-h_d^{t-1}+\underline{h}_d^{t-1})\end{aligned} \tag{2}$$

The first two terms in eq. (2) describe transitions where only the poverty status changes. As these transitions arise due to the mechanics of the Alkire-Foster-method, I denote their sum as $T_d^{mec} = P(PD|ND)\times(h_d^{t-1}-\underline{h}_d^{t-1}) - P(ND|PD)\times \underline{h}_d^{t-1}$, as they represent *mechanical* changes in $\Delta\underline{h}_d$.[7] In contrast, the sum of the other four *behavioural* transitions are denoted as T_d^{beh}. However, behavioural transitions can also be further distinguished into those where the deprivation, but not the poverty status changes, i.e. transitions taking place entirely *within* poverty $T_d^{wit} = P(PD|PN)\times(H^{t-1}-\underline{h}_d^{t-1}) - P(PN|PD)\times \underline{h}_d^{t-1}$ and those transitions where the change in deprivation helps to *determine* the poverty status, i.e. $T_d^{det} = P(PD|NN)\times(1-H^{t-1}-h_d^{t-1}+\underline{h}_d^{t-1}) - P(NN|PD)\times \underline{h}_d^{t-1}$ (the diagonal arrows in figure 1 a). Changes in censored headcount can thus also be written as

$$\Delta\underline{h}_d = T_d^{wit} + T_d^{det} + T_d^{mec}. \tag{3}$$

Alternatively, the transitions can also be group along the associated change of the poverty status, i.e. entries into poverty are $T_d^{p-entry} = P(PD|ND)\times(h_d^{t-1}-\underline{h}_d^{t-1}) + P(PD|NN)\times(1-H^{t-1}-h_d^{t-1}+\underline{h}_d^{t-1})$, exits from poverty are $T_d^{p-exit} = -P(ND|PD)\times\underline{h}_d^{t-1} - P(NN|PD)\times\underline{h}_d^{t-1}$ and transitions without change in the poverty status are T_d^{wit}. Thus, the change in the censored headcount can also expressed as

$$\Delta\underline{h}_d = T_d^{wit} + T_d^{p-entry} + T_d^{p-exit}. \tag{4}$$

[6] Alternatively, one could also study relative changes, which can be obtained by dividing both sides of eq. (2) by $\underline{h}_d^{t-1}$. For convenience the subsequent argumentation, however, uses absolute changes.
[7] Note that mechanical changes in some dimension d are not entirely mechanical in the sense that they are only produced by the method or the researcher. Instead, they are by-product of developments in other dimensions.

Decomposing ΔM_0. As the censored headcount can be written as $\underline{h}_d = T_d^{beh} + T_d^{mec}$ this can be substituted into (1) yielding the following helpful decomposition of M_0:

$$\Delta M_0 = \sum w_d (T_d^{beh} + T_d^{mec}) \tag{5}$$

Intuitively, the decomposition in eq. (5) reveals those changes in deprivation indicators that actually drive changes in multidimensional poverty, i.e. the 'real on-the-ground changes.' Section 5 provides graphical illustrations. Alternatively, also eq. (3) can be substituted into (1). Aggregating over dimensions (while accounting for weight and incidence) gives another interesting transition-based decomposition of ΔM_0:

$$\Delta M_0 = \sum w_d T_d^{wit} + \sum w_d T_d^{det} + \sum w_d T_d^{mec}. \tag{6}$$

Intuitively, eq. (6) partitions changes in M_0 into transitions that take place entirely within poverty (term 1), behavioural transitions that also change that headcount ratio H (term 2), and mechanical transitions resulting as by-product of exits and entries. In some sense eq. (6) can be viewed as another incidence-intensity breakdown of M_0. Finally, also eq. (7), which organizes transitions according to the associated change in the poverty status can also be substituted into (1). Rearranging terms then gives

$$\Delta M_0 = \sum w_d T_d^{wit} + \sum w_d T_d^{p-exit} + \sum w_d T_d^{p-entry}, \tag{7}$$

which is precisely what Alkire *et al.* (2015, p.274) suggest, based on the decomposition by dynamic subgroups. Note that dimensions may or may not be distinguished in this decomposition. Moreover, as transitions are net quantities opposed development may cancel out and terms in eq. (6) may have different signs.

Remarks on Mechanical Changes. Five brief remarks may help to better understand nature and relevance of mechanical changes. First, mechanical changes relate to the identification step in poverty and originate from the axiom of poverty focus. As soon as an individual's weighted deprivation count falls below the poverty cutoff her remaining deprivations must be ignored. This is normatively desired, since this person is, even though still deprived in some dimension, no longer poor. Second, substantially mechanical transitions are simply deprivations entered already previously. Hence a careful analysis of mechanical transitions can illuminate the accumulation process of deprivation. Third, as mechanical changes in dimensions result from poverty entries and exits, they become more important if either entries, or exits, or both become quantitatively more important. Thus, while a large ΔH indicates their relevance, a small ΔH does not preclude them. Fourth, mechanical changes are relevant for all k, except for a union approach, where an individual leaves poverty only with leaving her very last deprivation. Put differently, the union approach approach does not allow individuals to be non-poor, but d-deprived implying censored and uncensored headcounts to be identical and transitions of the type $PD \leftrightarrows ND$ not to exist.[8] Fifth, unless poverty exits are caused by simultaneous improvements in several dimensions, mechanical changes may well account for more than half of ΔM_0. Likewise, mechanical changes become by tendency more prevalent with increasing k, since people may leave poverty while 'taking more deprivations with them.'

Decomposing the Uncensored Headcount. Decomposing the uncensored headcount into the different transitions is important to better understand the link between multidimensional poverty and the dashboard approach in a dynamic setting and to evaluate the influence of an indicator-specific policy measure. The health department, for instance, may want to know to what extent an measure against child mortality also reached the poor.

Figure 1 (b) illustrates the relevant transitions for changes of the uncensored headcount ratio for a dimension d. Obviously, relevant transitions must involve a change in the deprivation status, which may or may not be accompanied with a change in poverty status. More formally, eq. (8) relates the changes in the uncensored headcount to its transition probabilities:

$$\begin{aligned}\Delta h_d = & -P(PN|PD) \times \underline{h}_d^{t-1} + P(PD|PN) \times (H^{t-1} - \underline{h}_d^{t-1}) \\ & -P(NN|PD) \times \underline{h}_d^{t-1} + P(ND|PN) \times (H^{t-1} - \underline{h}_d^{t-1}) \\ & -P(PN|ND) \times (h_d^{t-1} - \underline{h}_d^{t-1}) + P(PD|NN) \times (1 - H^{t-1} - h_d^{t-1} + \underline{h}_d^{t-1}) \\ & -P(NN|ND) \times (h_d^{t-1} - \underline{h}_d^{t-1}) + P(ND|NN) \times (1 - H^{t-1} - h_d^{t-1} + \underline{h}_d^{t-1}).\end{aligned} \tag{8}$$

Again, transitions can be grouped and labelled. First, observe that changes of uncensored headcounts, like changes of censored headcounts, also reflect the transition types T_d^{wit} and T_d^{det}, whereas T_d^{mec} are absent. Importantly, two further types of transitions can be distinguished. First, transitions in the deprivation status of non-poor, which do not affect their poverty status, i.e. they take place entirely *outside* poverty: $T_d^{out} = P(ND|NN) \times (1 - H^{t-1} - h_d^{t-1} + \underline{h}_d^{t-1}) - P(NN|ND) \times (h_d^{t-1} - \underline{h}_d^{t-1})$. And second, transitions in deprivation that

[8]Accordingly, M_0 can be decomposed into the *un*censored headcounts only for union identification (Alkire and Foster, 2011a, p.482), implying a 'factor decomposability' in the sense of Chakravarty *et al.* (1998, p.179).

run counter to the change in the poverty status, as transitions in other dimensions *dominate* the change in d, i.e. $T_d^{dom} = P(PD|NN) \times (1 - H^{t-1} - h_d^{t-1} + \underline{h}_d^{t-1}) - P(PN|ND) \times (h_d^{t-1} - \underline{h}_d^{t-1})$. While empirically observable this sort of transitions may be negligible in certain scenarios. As dominated transitions, like mechanical transitions rely on developments in other dimensions, both may be considered as more complex interdependencies among dimensions in multidimensional poverty measurement.

Similar to censored headcount ratios, uncensored headcounts can also be partitioned into different transitions, such as

$$\Delta h_d = T_d^{wit} + T_d^{out} + T_d^{det} + T_d^{dom}. \tag{9}$$

Eq. (9) essentially shows that changes in single indicators may either (i) change the only the intensity of poverty among the poor, (ii) change in line with the poverty status, (iii) may not affect the poor at all, or (iv) are overlayed by changes in other dimensions such that transitions in d change counter to the poverty status. Alternatively, the transitions involving a change in poverty status, i.e. T_d^{dom} and T_d^{det} can also be regrouped such that the direction of that change is indicated, i.e. entries and exits.

$$\Delta h_d = T_d^{p-entries} + T_d^{wit} + T_d^{out} + T_d^{p-exit} \tag{10}$$

Eq. (10) may, for instance, reveal large quantities in d-related entries and exits of poverty (e.g. due to unemployment), which may cancel out if only Δh_d is studied. Both eq. (9),(10) help to better understand how the poor are affected by, say, the overall decrease of child mortality or the increase in unemployment. Section 5 provides illustrations.

Censored and Uncensored Headcount Ratios. The dashboard approach studies changes indicator by indicator, i.e. uncensored headcount ratios. Changes in multidimensional poverty are often decomposed into dimensional changes to better understand why exactly multidimensional poverty changed. There are two important questions which demand a better understanding how changes in censored and uncensored headcount ratios are related. First, whether the identification step in multidimensional measurement offers additional insights for studying changes in dimensions and second, whether changes in uncensored headcount ratios can support the analysis of changes in censored headcounts if only repeated cross-sectional data is available. Answering both questions rests upon a thorough understanding which transitions are reflected by each quantity and due to which transitions they may differ. Figure 1 and eq. (3),(9) clearly reveal that both censored and uncensored headcounts reflect transitions of deprivations which either take place within poverty (T_d^{wit}) or change the poverty changes (T_d^{det}). Taking their difference, however, clearly reveals that there are several reasons for why both quantities might suggest different developments:

$$\Delta h_d - \Delta \underline{h}_d = T_d^{out} + T_d^{dom} - T_d^{mec} \tag{11}$$

Eq. (11) identifies three major sources for why h_d and $\underline{h}_d$ may differ: first, only the uncensored headcount reflects transitions in d, which do not affect the poor at all or, second, those transitions which are dominated by changes in other dimensions. Third, only the censored headcount reflects changes, say decreases, due to improvements in the other dimensions, even though no on-the-ground change in d takes place. Also note that eq. (11) refers to net transitions, which consequently may be positive or negative. Thus, T_d^{mec} may increase or decrease the difference and importantly, add to T_d^{out} or run counter to it.

If the goal is to uncover eventual behavioural differences between the changes in plain indicators and how changes in dimensions affect the poor, it is convenient to focus on 'on-the-ground changes', i.e. T_d^{beh}. However, even if T_d^{mec} are ignored, eq. (11) shows that different conclusions may still emerge for several reasons. First, poor may be affected systematically different from non-poor, in the sense that, e.g., d-deprived poor are less likely to leave deprivation d, than non-poor but d-deprived persons (see also section 4.1). Relatedly, changes in the uncensored headcount ratio may largely reflect changes among non-poor, which among other things also depends on the relative sizes of H^{t-1}, h_d^{t-1}, and $\underline{h}_d^{t-1}$.[9] For instance, a dashboard approach, would always indicate an improvement if, say, the unemployment rate goes down. However, it remains unclear whether or not the poor (i.e. the multiply deprived) benefited as well. In fact, one may expect a systematic difference in the case of unemployment, as the poor often also suffer from bad health or low education and are, therefore, less likely to find a job during economic recovery. Moreover, the difference may result from dominated transitions, i.e. due to more complex interdependencies among dimensions. If for instance, a non-poor unemployed finds employment, but simultaneously enters deprivations in say health and housing, which render him poor, then only the uncensored headcount ratio would reflect this transition.[10]

While this line of thought suggests that unique insights can be obtained using methods of multidimensional poverty measurement, at the same time they also suggest that uncensored headcount ratio can offer only limited back-up for analyses with repeated

[9] Note that the first aspect presumes a difference in the conditional probabilities, while the second results from the respective proportions, i.e. the factors the conditional probabilities are multiplied with.
[10] However, censored headcount ratios of housing and health would, of course, register these changes.

cross-section data. First note that relying exclusively on changes in censored headcounts, may produce a distorted picture, as mechanical transitions complicate the analysis. If, for instance, several successful policy measures have been adopted, which result in several decreasing censored headcounts (on-the-ground changes), unsuccessful and futile attempts to improve say health go easily undetected. If many poor people are deprived in health, the censored headcount ratio of health may decrease for the improvements in the other dimensions (i.e. due to mechanical changes). Even increases in health deprivation may be overlayed by such developments. As policy failures may go undetected this produces an incentive problem for policy makers. Therefore, it is important to obtain credible estimates of mechanical changes. A natural starting point is to compare changes in censored and uncensored headcount ratios. However, as explained above censored and uncensored headcount ratios may differ for several reasons, and not only due to mechanical transitions. Thus an analysis with repeated cross-sections requires additional assumptions, which is resumed in 4.3.

4 Related Analyses

4.1 Are poor more likely to enter another deprivation?

Two related questions that can be studied with panel data are whether not-d-deprived poor and not-d-deprived non-poor face the same probability for entering a deprivation d and, conversely, whether poor and non-poor d-deprived face the same probability to leave that deprivation. These questions are interesting as multidimensional poverty measurement implicitly assumes that deprivations may accumulate under certain conditions. Answering this question would offer some first descriptive evidence on such a presumption. Moreover, if there was no systematic difference, i.e. if poor and non-poor faced the same probability of entering (leaving) a deprivation, multidimensional poverty measures would add little extra insight on the *dynamics*, since analyses of dimensional changes pre- and post identification may offer less contrasting conclusions.

Theoretically, various mechanisms may produce such a systematic differentiated influence. Low educational achievements in households, for instance, may reduce the probability of the children's school attendance or finding a new job. Alternatively, poor may also be more likely to suffer permanently from various economic shocks (which may manifest in asset indicators). Likewise, certain other background factors may produce such a finding. On the other hand, if introduced, a well-targeted anti-poverty policy could produce the opposite pattern, meaning that poor are more likely to leave certain deprivations than non-poor.

To test for such a differentiated influence one can construct odds-ratios using the conditional probabilities, where deprivation inflow and outflow have to be distinguished, i.e.

$$r_d^{out} = \frac{P(PN_d^t|PD_d^{t-1}) + P(NN_d^t|PD_d^{t-1})}{P(PN_d^t|ND_d^{t-1}) + P(NN_d^t|ND_d^{t-1})} \tag{12}$$

The numerator contains the conditional probabilities of a poor and d-deprived individual to leave the d-deprivation—either while remaining poor or while leaving poverty entirely. Non-poor but d-deprived may either leave the deprivation and remain non-poor, or become poor due to deprivations in other dimensions. Accordingly, the denominator contains these conditional probabilities for the non non-poor but d-deprived individual. In terms of figure 1, r_d^{out} compares the transitions starting at PD with those starting at ND. The deprivation inflow ratio r_d^{in} in d can be constructed analogously:

$$r_d^{in} = \frac{P(PD_d^t|PN_d^{t-1}) + P(ND_d^t|PN_d^{t-1})}{P(PD_d^t|NN_d^{t-1}) + P(ND_d^t|NN_d^{t-1})} \tag{13}$$

Importantly, if d-deprived (not-d-deprived) are equally likely to leave (enter) the deprivation in d, r_d^{out} (r_d^{in}) equals 1. Testing this presumption with real-world data is an important exercise as it facilitates the analysis with repeated cross-section data (see section 4.3). Evidence on systematically different chances to leave (enter) deprivations by poverty status, would also complement the poverty cutoff with a substantial or behavioural interpretation. Naturally, the normative nature of setting the k-cutoff remains unaffected. Finally, such evidence also deepens the understanding of potentially inconclusive findings of multidimensional poverty measures and dashboards on the assessment of changes over time.

4.2 Scrutinizing Poverty Entries and Exits

Panel data allow to study entries and exits of poverty more carefully. Assuming a 2-year panel for simplicity, Alkire *et al.* (2015, pp.273–276) first partition the panel into dynamic subgroups (ongoing poor, non-poor, exits and entries). Then dimensional decompositions can be analysed for each point in time separately or together (i.e. the change). Apablaza and Yalonetzky (2013), in contrast, calculate entry and exit probabilities more generally and show for instance how these vary with k, the poverty cutoff.

The transitional perspective explored in this paper, goes one step further in the analysis of poverty entries and exits. Specifically, panel data allows also to distinguish deprivations that made an individual cross the k-cutoff from deprivation that were entered already previously. Put differently, what is to be distinguished are behavioural and mechanical transitions among those who enter (or leave) poverty. Such analyses offer valuable insights on the process of how deprivations accumulate: Are there certain deprivations that frequently set the stage for entering poverty, while other deprivations make an individual finally cross the cutoff? Which deprivation tend to be more persistent, and which not? A natural way to study these questions is to calculate the share of mechanical and behavioural transitions *into* a deprivation among those who *enter* poverty, or formally:

$$s^{p+}_{d\text{-beh}} = \frac{P(PD|NN) \times (H^{t-1} - h^{t-1}_d + \underline{h}^{t-1}_d)}{P(c^t_i \geq k | c^{t-1}_i < k) \times (1 - H^{t-1})} \quad \text{and} \quad s^{p+}_{d\text{-mec}} = \frac{P(PD|ND) \times (h^{t-1}_d - \underline{h}^{t-1}_d)}{P(c^t_i \geq k | c^{t-1}_i < k) \times (1 - H^{t-1})}. \tag{14}$$

Likewise the share of mechanical and behavioural transitions *out of* deprivations among those who *leave* poverty is calculated as:

$$s^{p-}_{d-beh} = \frac{P(NN|PD) \times \underline{h}^{t-1}_d}{P(c^t_i < k | c^{t-1}_i \geq k) \times H^{t-1}} \quad \text{and} \quad s^{p-}_{d-mec} = \frac{P(ND|PD) \times \underline{h}^{t-1}_d}{P(c^t_i < k | c^{t-1}_i \geq k) \times H^{t-1}}. \tag{15}$$

Note that the shares of behavioural transitions may sum up to more the 100%, as crossing the poverty cutoff may be caused by one or by several deprivations. Section 5 provides an illustration.

4.3 Analysing changes using cross-sectional data

In practice, however, panel data are often still lacking. Thus the question of how to study dimensional dynamics in multidimensional poverty using repeated cross-sectional data arises. As explained before, censored and uncensored headcount ratio each offers only a limited insight into the dimensional changes which really affect the lives of the poor. A natural way-out may rely on both quantities simultaneously, raising the question what can be inferred from comparing censored and uncensored headcount about behavioural transitions or on-the-ground changes. The difference between uncensored and censored headcount ratios in eq. (11), however, reveals that both quantities may differ for different reasons. In particular changes in d may only affect non-poor, or developments in other dimensions change the poverty status, thereby producing mechanical transitions. Note that even a simultaneous decrease in both censored and uncensored headcount of a dimension does not imply that poors' life improved due to on-the-ground changes in that dimension.

Assume, for instance, the department of health successfully implements a broad health reform, which removes deprivation in health for both poor and non-poor. Some person may also leave poverty entirely, although still unemployed. If during the evaluation period, the department of labour also implements a labour market reform, which also successfully reduces the unemployment rate, we may observe decreasing uncensored and censored headcount ratios for both health and unemployment. One may be tempted to conclude, that the labour market reform was also a success in fighting poverty. This conclusion is, however, not warranted, because the beneficiaries of labour market reform might have been largely non-poor people (which is not unreasonable), whereas the decrease in censored headcount of unemployment is solely to mechanical transitions, induced by the successful health reform.

The difference of uncensored and censored headcount can not only be expressed in transitions like in eq. (11), but also in terms of transition probabilities:

$$\begin{aligned}\Delta h_d - \Delta h_d(k) = & P(ND_d^t|PD_d^{t-1})h_d^{t-1}(k) + P(ND_d^t|PN_d^{t-1})(H^{t-1} - h_d^{t-1}(k)) \\ & + P(ND_d^t|NN_d^{t-1})(1 - H^{t-1} - h_d^{t-1} + h_d^{t-1}(k)) \\ & - [P(PD_d^t|ND_d^{t-1}) + P(PN_d^t|ND_d^{t-1}) + P(NN_d^t|ND_d^{t-1})](h_d^{t-1} - h_d^{t-1}(k)),\end{aligned} \tag{16}$$

or graphically, as shown in figure 2. Both figure 2 and eq. (16), suggest that without additional information, we cannot infer much by comparing uncensored and censored headcount ratios. The reasons are (i) that the difference is shaped by three different types of transitions and (ii) that each of these transitions are net quantities, i.e. their sign is in general undetermined. However, under certain assumptions credible estimates of behavioural and mechanical transitions may be obtained. Support for such assumptions may come from the data at hand, theory, external resources or previous research.

Figure 2: The difference between censored and uncensored headcounts

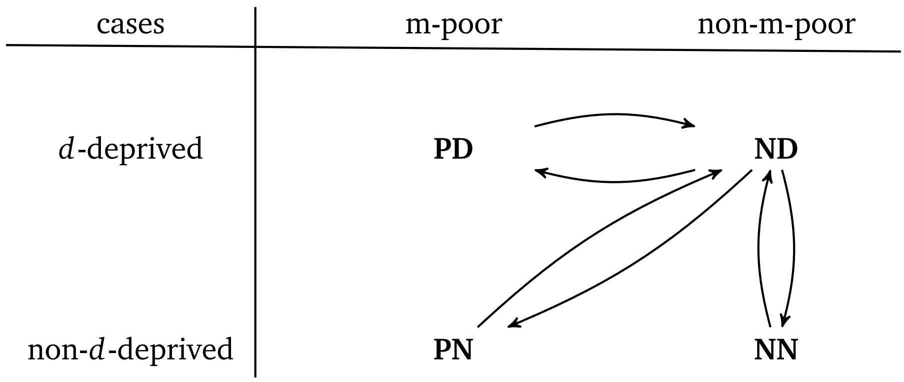
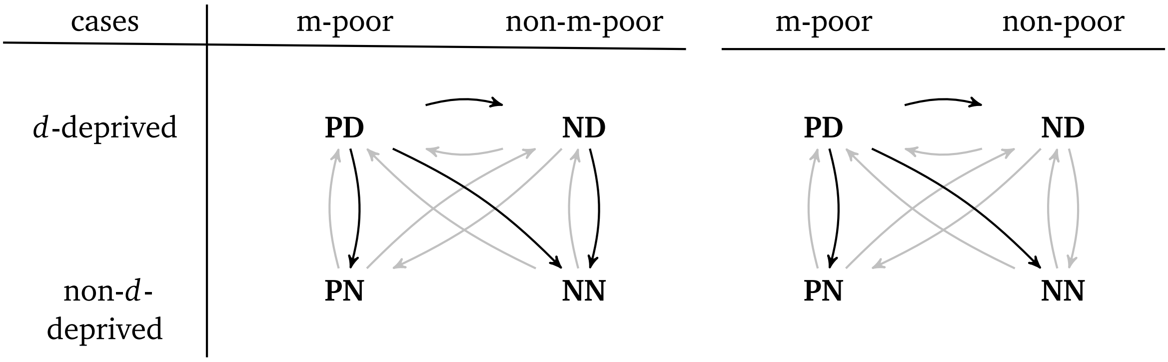


Figure 3: Scenarios



(a) Scenario A **(b) Scenario B**

Scenario A. To illustrate how such a scenario-based inference may work, two such cases are briefly discussed. In scenario A all indicators, i.e., uncensored headcount ratios, are decreasing, which is a common situation in many countries, see Alkire *et al.* (2014b). To fix ideas assume, moreover, no entries into deprivations, counter to the overall decreasing trend. Then from all relevant transitions, which affect the difference of censored and uncensored headcount ratios, only four remain, as illustrated by the black arrows in figure 3 (a). The other transitions are ruled out by assumption: specifically, nobody enters a deprivation ($\rightarrow PD, \rightarrow ND$), dominated changes cannot occur either ($PN \leftrightarrows ND$), as all indicators change in the same direction, neither can somebody enter poverty due changes in other deprivations, i.e. $ND \rightarrow PD$ cannot occur. Applying these assumptions to eq. 16, solving for the mechanical transitions and using definition of r_d^{out} gives

$$P(ND|PD)\underline{h}_d^{t-1} = \frac{\underline{h}_d^{t-1} r_d^{out}}{h_d^{t-1} + \underline{h}_d^{t-1}(r_{out}^d - 1)} \Delta h_d - \Delta \underline{h}_d \tag{17}$$

Recall that r_d^{out} describes the probability to leave a deprivation for the poor, relative to that probability for the non-poor. Assuming for now no difference in exiting a deprivation, ie $r_d^{out} = 1$ reduces our estimate to

$$T_d^{mec} = -P(ND|PD)\underline{h}_d^{t-1} = \Delta \underline{h}_d - \frac{\underline{h}_d^{t-1}}{h_d^{t-1}} \Delta h_d \tag{18}$$

Intuitively, we correct the observed change in the censored headcount, by the fraction of the change in the uncensored headcount that would affect the poor and deprived if both non-poor and poor are equally likely to leave the deprivation. Obtaining $T_d^{mec} < 0$ then means that the observed change in $\underline{h}_d$ cannot be fully 'explained' by the change in the uncensored headcount ratio. Hence this residual must be due to mechanical changes, i.e. improvements in other dimensions.

Scenario B. In Scenario B only the key indicator is decreasing, but also $\underline{h}_d^{t-1} = h_d^{t-1}$. Moreover, no deprivation entries opposing the trend take place. The assumption of $\underline{h}_d^{t-1} = h_d^{t-1}$ reduces the group ND to 0 implying that no transitions can start from there. As the key indicator is decreasing and there no entries counter that trend we are left with three types of transitions. Applying the assumption to eq. 16 gives (see also figure 3):

$$T^{mec} = -P(ND|PD)h_d^{t-1} = -(\Delta h_d - \Delta \underline{h}_d) \qquad (19)$$

Intuitively, any change in the uncensored headcount must be reflected in the censored headcount, too. Changes beyond that then must be due to developments in other dimensions.

5 Evidence from Germany

Data and Specification. The empirical analyses in this section uses data of the German Socio-Economic Panel (Wagner *et al.*, 2007). The chief purpose is to present a year-to-year analysis of multidimensional poverty using the panel data-based decompositions above. To balance competing requirements (e.g, availability of indicators, comprehensibility of the analysis), I confine the analyses to the data waves for 2005 and 2007. This allows a reasonable multidimensional poverty index and a focus on an easy to manage period. Note, however, that Suppa (2015) suggests a more comprehensive specification for Germany (along with a more detailed justification), but the present one also serves the purpose intended. Table 1 summarizes the adopted specification, i.e. the selected functionings, the deprivation indicators, their cutoffs and weights. Dimensions are weighted equally as are most indicators within dimensions. Ultimately, only the indicators for unemployment and low education receive a higher weight, as each indicator represents a deprivation in an entire dimension. Finally, the sample is restricted to individuals aged 18 or above and observations are weighted with their inverse sampling probability to account for the complex survey design.

Table 1: Specification of the Multidimensional Poverty Index.

Functioning	Deprivation cutoff	Variable	Weight
Education	left school without graduation or graduation but no vocational qualification[a]	dep_educ	1/6
Housing	any of bath, kitchen, water, or toilet is missing	dep_hhfacilities	1/12
	less than 1 room per person in household	dep_overcrowded	1/12
Health	partially or severely disabled	dep_disability	1/12
	respondent reports her health to be *poor* or *bad*	dep_health	1/12
Precarity	reporting 2/4 goods missing for financial reasons[b]	dep_matdep	1/12
	precariously employed (incl. temporary work)	dep_precemp	1/12
Social Participation	at least 5/7 activities are performed *never*; remaining at most *less than monthly*[c]	dep_actindex	1/12
	respondent report to *never* meet her friends	dep_meetfriends	1/12
Employment	registered unemployed	dep_unemp	1/6
	working less than 30 hours a week, but desiring to work more	dep_underemp	1/12

Notes: [a] Graduation in Germany is usually achieved after 10 years of schooling. [b] The four goods asked for are (i) a warm meal, (ii) whether friends are invited for dinner, (iii) whether money is put aside for emergencies, and (iv) whether worn out furniture is replaced. [c] Activities included are (i) going to the movies, pop music concerts, dancing, disco, etc, (ii) going to cultural events (such as concerts, theater, lectures), (iii) doing sports yourself, (iv) volunteer work, (v) attending religious events, (vi) helping out friends, relatives or neighbours (vii) involvement in a citizens' group, political party, local government.

Elementary Analyses. Table 2 (a) shows levels and changes for every single indicator. A dashboard approach analysis would exclusively rely on information like these. Deprivation levels vary in part substantially ranging from ca. 1.5% in $dep\_hhfacilities$ to more than 15%, e.g., in health, material deprivation, or social activities. Moreover, Table 2 contains also their changes over time (absolute and relative), showing both housing indicators ($dep\_overcrowded$ and $dep\_hhfacilities$), unemployment and underemployment to decrease from 2005 to 2007. The remaining indicators are all increasing.[11] Specifically, the unemployment rate falls from 6.1% to 5.1%, which is approx. 1%-point in absolute terms and ca. 20% in relative terms. While each absolute and relative changes emphasize different aspects of changes, the subsequent analysis will mostly draw on absolute changes for expositional convenience.

Table 2 (b) shows indices of multidimensional poverty along with their changes, both absolute and relative, and for two different values of k. For instance, using a poverty cutoff of $k = 33$ ca. 10.0% were poor in 2005 and 10.8% in 2007, i.e. the poverty headcount increased by 0.8%-points or by 7.5%. The adjusted headcount ratio M_0 increases from 0.03911 to 0.0424, i.e. by 0.0032 and much of the subsequent analysis will try to better understand why. Note, that this increase of poverty is independent of k. Finally, table 2 (b) also contains the censored headcount ratios (which depend on k) along with their changes. First, note that levels of censored headcounts are substantially smaller than levels of uncensored headcounts, implying that a substantial part of the deprivations indicated by the dashboard approach are deliberately ignored, once the focus is on the multiply deprived (i.e. through identification). For instance, while ca. 15% are deprived in education according to the uncensored headcount ratio, only 7% are deprived in education according to the uncensored headcount ratio. Second, observe that the signs of changes in censored and uncensored headcounts do not necessarily match (e.g. $dep\_hhfacilities$). Moreover, some changes differ quantitatively and thus seem to tell different stories. Deprivation in education for instance increases 0.067%-points in the total population (which is rather little compared to other indicators), whereas the share of education-deprived poor increases by 0.57%-points, which is not only larger by a factor of 8, but also a considerable change compared to other indicators. Note that thus far censored and uncensored headcount ratios provide rather inconclusive evidence and render a consistent evaluation of the underlying developments difficult. The suggested panel data-based decompositions, however, allow to probe the causes of these observations.

[11] A more substantial interpretation of the evidence requires additional years with data. It should be noted, however, that the years of investigation cover among other things a major labour market reform.

Table 2: Indicators, Indices and Contributions of Multidimensional Poverty

(a) Dashboard (uncensored headcount ratios)

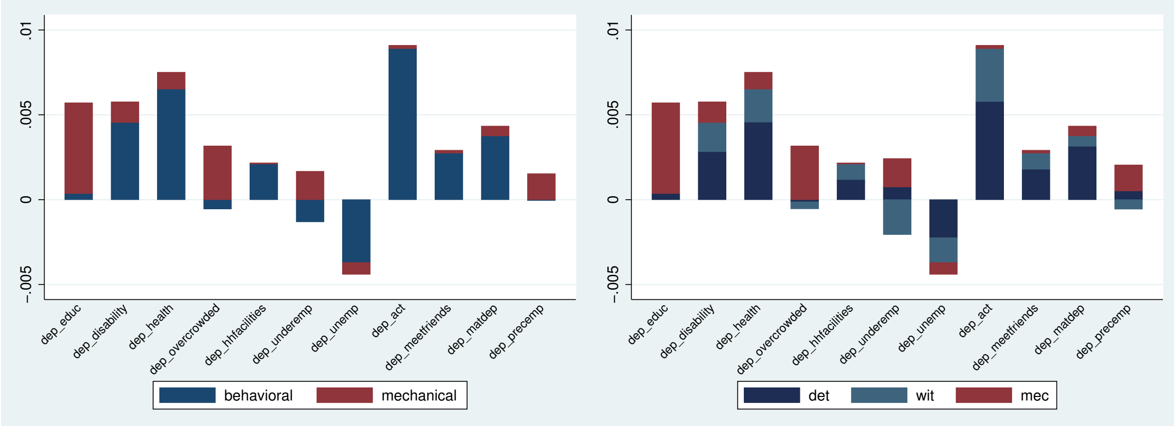
	2005	2007	Δ	δ
dep_educ	0.14924	0.14991	0.00067	0.00447
dep_disability	0.13528	0.14878	0.01350	0.09982
dep_health	0.19090	0.20971	0.01881	0.09852
dep_overcrowded	0.06056	0.05390	-0.00667	-0.11008
dep_hhfacilities	0.01563	0.01515	-0.00048	-0.03079
dep_unemp	0.06135	0.05141	-0.00995	-0.16211
dep_underemp	0.09658	0.09304	-0.00354	-0.03667
dep_precemp	0.05955	0.06260	0.00306	0.05133
dep_matdep	0.17462	0.18944	0.01482	0.08485
dep_act	0.19399	0.21467	0.02068	0.10662
dep_meetfriends	0.02545	0.03127	0.00582	0.22866

(b) Aggregate Indices of Multidimensional Poverty

	2005		2007		Δ		δ	
	$k = 33$	$k = 41$	$k = 33$	$k = 41$	$k = 33$	$k = 41$	$k = 33$	$k = 41$
M_0	0.03911	0.02084	0.04235	0.02354	0.00324	0.00270	0.08282	0.12950
H	0.10023	0.04542	0.10779	0.05136	0.00756	0.00594	0.07545	0.13083
A	0.39023	0.45889	0.39290	0.45835	0.00267	-0.00054	0.00685	-0.00118
dep_educ	0.0676	0.0368	0.0733	0.0408	0.0057	0.0039	0.0845	0.1062
dep_disability	0.0349	0.0200	0.0406	0.0218	0.0058	0.0018	0.1654	0.0917
dep_health	0.0576	0.0287	0.0651	0.0342	0.0075	0.0055	0.1304	0.1935
dep_overcrowded	0.0162	0.0088	0.0188	0.0109	0.0026	0.0022	0.1620	0.2467
dep_hhfacilities	0.0041	0.0023	0.0063	0.0041	0.0022	0.0018	0.5273	0.7836
dep_unemp	0.0320	0.0177	0.0276	0.0171	-0.0044	-0.0006	-0.1373	-0.0333
dep_underemp	0.0154	0.0069	0.0157	0.0077	0.0004	0.0008	0.0239	0.1167
dep_precemp	0.0118	0.0051	0.0133	0.0052	0.0015	0.0001	0.1259	0.0227
dep_matdep	0.0588	0.0299	0.0631	0.0339	0.0043	0.0041	0.0738	0.1356
dep_act	0.0573	0.0305	0.0664	0.0374	0.0091	0.0069	0.1586	0.2255
dep_meetfriends	0.0141	0.0090	0.0170	0.0115	0.0029	0.0025	0.2068	0.2826

Notes: Data From SOEP.

Figure 4: Decomposing Censored Headcount Ratios

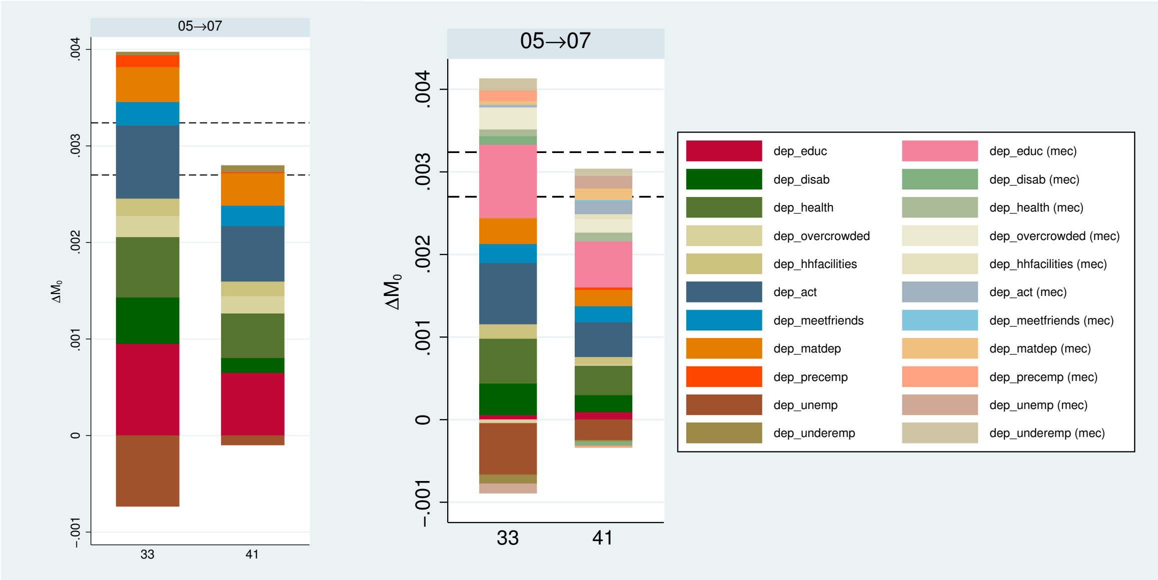


Notes: Data from SOEP. Units are absolute changes of (censored) deprivation headcount ratios, e.g., deprivation in social activities dep_act increases by ca. 0.9%-points.

Decomposing the Censored Headcount Ratio. In the first step eq. (3) and (4) prove useful to better understand the dynamics behind these first observations. The left graph of figure 4 reveals three particular interesting aspects: First, the increase in the censored headcount of dep_educ (and $dep\_precemp$ as well) is entirely due to mechanical transitions. Second, in some cases mechanical transitions add to behavioural, i.e. they change the censored headcount ratio into the same direction (e.g. for disability or health), while in other cases mechanical changes run counter to behavioural changes (e.g., for $dep\_overcrowded$ or underemployment). Even though quantitatively small these observations illustrate potential complexities which may emerge in the course of an analysis. The right graph of figure 4 additionally distinguishes behavioural transitions according to whether the poverty status changed (T_d^{det}) or whether individual remains poor (T_d^{wit}). Leaving unemployment, for instance, was frequently accompanied by leaving poverty entirely, but not always. Some people, however, left poverty, albeit being still unemployed. In contrast the reduction of social activities made several individuals cross the poverty cutoff, and a remarkable amount of people entered this deprivation, while already poor. Few people left poverty, despite a continuing deprivation in social activities.

Decomposing the Adjusted Headcount Ratio. Changes in dimensions can also be more precisely related to changes in the adjusted headcount ratio through dimensional breakdowns. The left graph in figure 5 contains conventional dimensional breakdowns of the absolute change in the adjusted headcount ratio (ΔM_0) for different poverty cutoffs, see eq. (1). Dimensional contributions in this decomposition reflect the weighting scheme.

Figure 5: Decomposing the Adjusting Headcount Ratio.



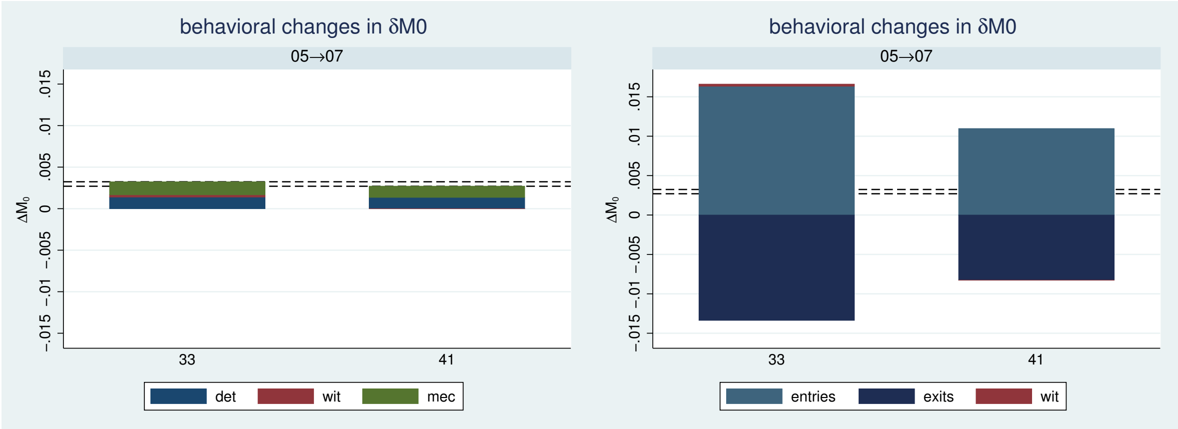
Notes: Data from SOEP. Poverty cutoffs are $k = 33, 41$. Dashed lines indicate the total change in M_0.

Consequently, changes in censored headcount ratios of unemployment and education are relatively magnified.[12] The graph also signals potential differences in the directions of changes immediately. Taken as a whole this decomposition is a useful starting point to probe the causes of ΔM_0. Since changes censored headcount ratios can be decomposed into behavioural and mechanical transitions, contributions to ΔM_0 can be too. The right graph of figure 5 shows the results. Specifically, it reflects several of the previous insights, e.g., that the increase in dep_educ (but also $dep\_precemp$) among the poor is largely due to mechanical transitions and, at the same time it, reflects the weighting scheme. While this sort of graph can easily become confusing for more dimensions, it still offers a concise way which covers many important insights.

Figure 6, instead, shows two other decompositions of ΔM_0, of which the left uses eq. (6) and the right eq. (7). The slight increase for the period under investigation results mostly from net entries into poverty, partly due to new deprivations ($\sum T_d^{det}$) and partly due to older deprivations ($\sum T_d^{mec}$). Net changes among the poor apparently contribute little. The right graph of figure 6 reveals that considerable entries into and exits out of poverty affect M_0, which however offset each other and thus imply the rather modest net increase. An analysis ignoring this point must certainly be considered incomplete.

[12]Naturally, this analysis becomes more important if more indicators are weights differently.

Figure 6: Decomposing the Adjusted Headcount Ratio II

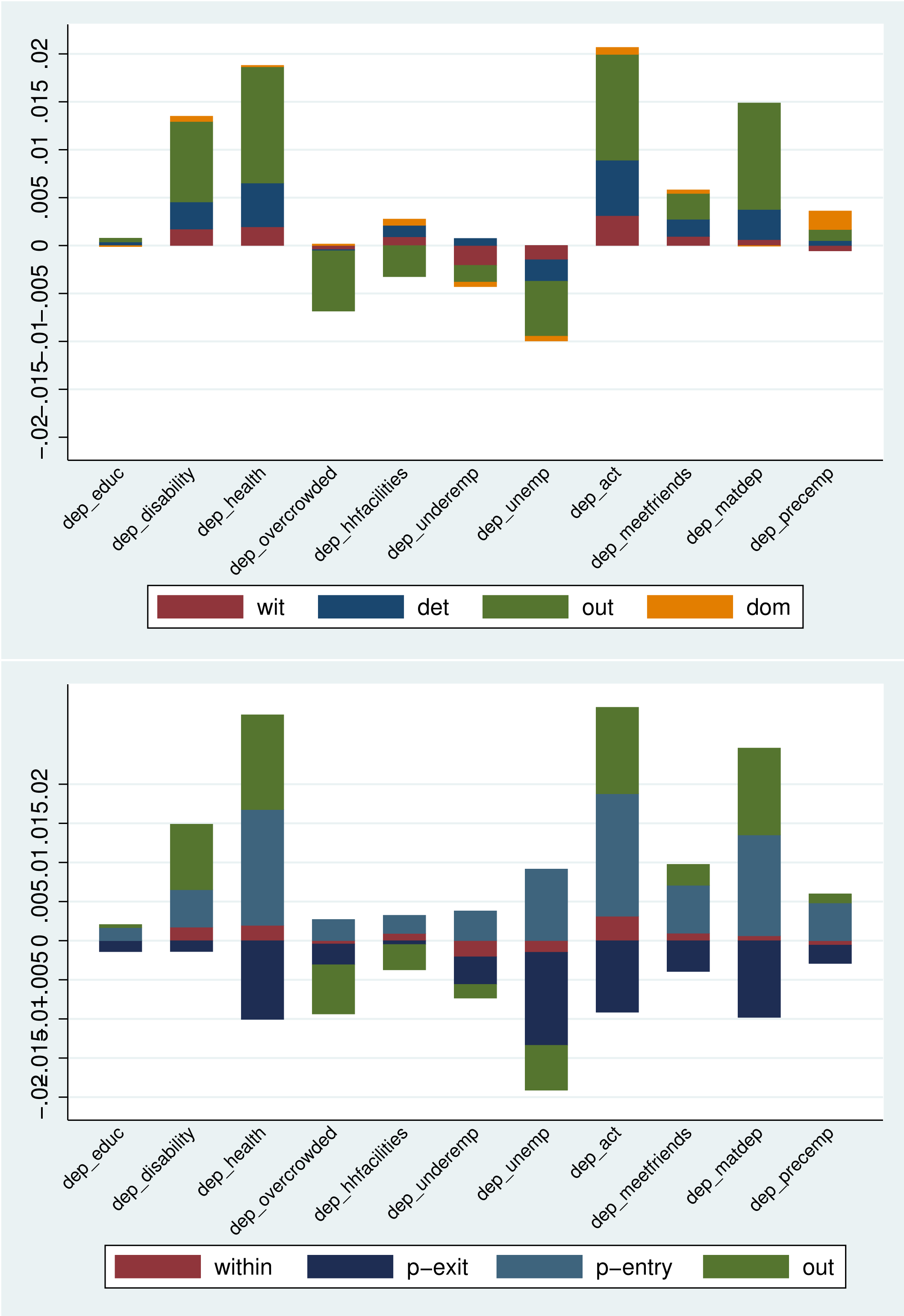


Notes: Data from SOEP. Dashed lines are ΔM_0 for $k = 33, 41$.

Decomposing the Uncensored Headcount Ratio. Decomposing the uncensored headcount entails a shift in perspective. The department for labour may want to know to what extent 'their' indicators are responsible for entries into poverty, or whether it improves or worsens the lives of the poor, or whether it mainly affects non-poor. Figure 7 contains two possible decompositions of Δh_d. The upper one, using eq. (9), shows that much of the indicator-specific transitions affect the non-poor, i.e. transitions in deprivations collected in T_d^{out}.[13] Figure 7 also shows that dominated transitions sometimes do matter, e.g., in $dep\_precemp$, as people become deprived due starting work under precarious conditions, while at the same time leaving poverty due to improvements in other dimensions, which in this particular case might be unemployment. In contrast, other indicators clearly worsen the lives of the already poor (dep_act, $dep\_meetfriends$) and in sum also increase the number of poor people. The reduction of unemployment, however, largely improved the lives of the non-poor, but also improved the situation of some multiply deprived, though still poor and finally allowed yet others to leave poverty entirely. Also note that some deprivation indicators may have more complex effects, as e.g., $dep\_hhfacilities$ or $dep\_underemp$. The lower graph, using eq (10), distinguishes entries and exits revealing that remarkable amounts of entries and exits may hide behind the net-quantities. The unemployment-induced entries into poverty, for instance, have a magnitude equivalent to an almost 1%-point increase of the unemployment rate. Thus a considerable amount of people enters unemployment and poverty, despite the net improvement.

[13] Note that this proportion of outside-poverty-transitions in deprivations by tendency increases with k.

Figure 7: Decomposing the Uncensored Headcount Ratio

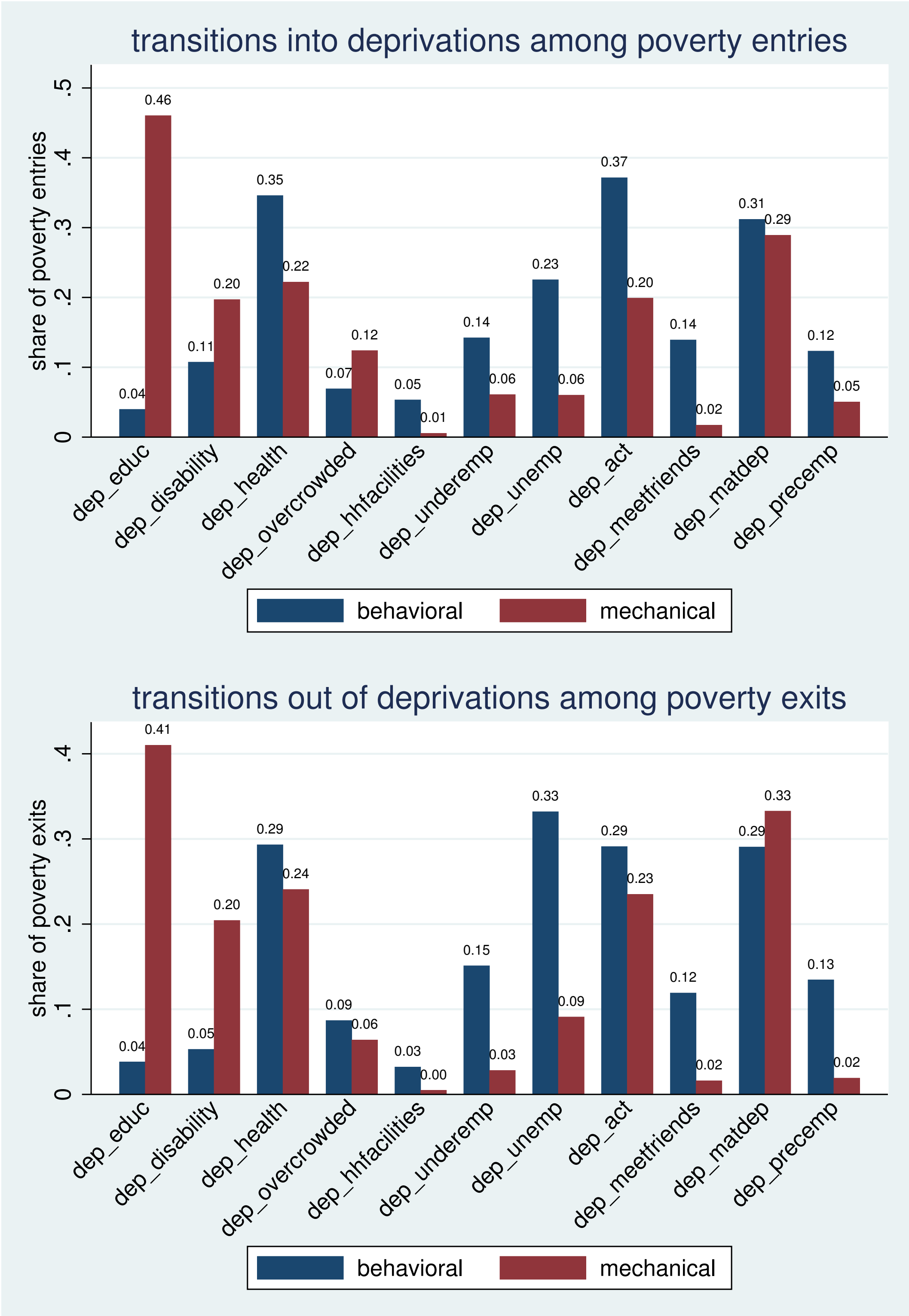


Notes: Data from SOEP. Underlying poverty cutoff is $k = 33$.

Entries and Exits of Poverty. Figure (8) provides a more in-depth analysis on poverty entries and exits. More specifically, the upper (lower) graph contains the shares of transitions into (out of) deprivations experienced by those entering (leaving) poverty. For instance, 46% of all individuals who entered poverty were already deprived in education in the first place, while 23% became poor when they became unemployed. Note that even percentages of behavioural transitions sum up to more than 100%, in fact ca. 180%, since many individuals enter several deprivations simultaneously. Broadly speaking, three different patterns are striking. First, some deprivations, like education and disability, appear to matter for both entries and exits only indirectly in the sense that they increased the counting vector in the first place, while other deprivations shift the deprivation count above the k-cutoff. Likewise few people leave poverty because of leaving deprivation in education (4%) or disability (5%), rather most people who leave poverty remain deprived in education (41%) or disability (20%). Thus, both deprivations are entered relatively early and also appear to be persistent. Other deprivations, like unemployment or underemployment seem to play a particular role in entering and leaving poverty, e.g., only 9% of individuals who managed to leave poverty did so while still deprived in unemployment, while 33% percent who left poverty also left unemployment. Finally, deprivations like material deprivation seem to play an dual role: while 31% become poor due to material deprivation, another 30% were deprived in material deprivation before ultimately entering poverty. Thus deprivations like these may happen earlier or later in the process of accumulating deprivation—sometimes they are setting the stage, sometimes they are directly pushing the deprivation count above the critical threshold. Material deprivation and unemployment both seem to be less persistent than deprivations in education or disability.

Relative Performance in Deprivation Transitions. The last empirical exercise provides evidence on the question raised in section 4.1, whether poor are more likely than comparable non-poor to enter another deprivation and less likely to leave a certain deprivation. Figure 9 (a) shows that the odds for leaving a given deprivation are smaller than 1 for most indicators and independent of k. Thus, poor are for instance only ca. half as likely as non-poor to leave a deprivation in education. Panel (b) on the other hand, reveals poor to be more likely than non-poor to enter another deprivation (both conditional on being non-deprived) since most odds are lager than 1, in fact several odds are twice as large or more. Note, however, that even though this pattern is seems systematic, it is purely descriptive and demands further theoretical explanation. Finding a good job, for instance, may be easier for healthy and educated persons entertaining effective social networks. Conversely,

Figure 8: Mechanical and Behavioural Transitions among Poverty Entries and Exits



Notes: Data from SOEP. Underlying poverty cutoff is $k = 33$.

bad health, unpleasant housing conditions, or recent unemployment may reduce meeting friends and other social activities. Whatever the underlying mechanisms, the results suggest that accumulated deprivations attract further deprivations.

6 Concluding Remarks

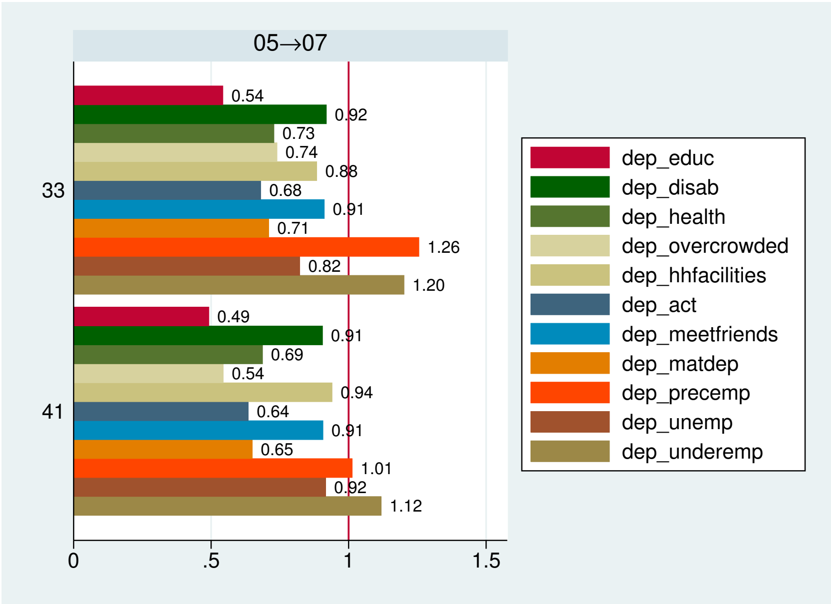
In place of another summary, I conclude with some final remarks. First, this paper underlines the benefits of multidimensional poverty measures, which fulfill dimensional breakdown and subgroup decomposability. Together both features allow a joint analysis of transitions in deprivations and poverty, which enable the analyst to handle potentially complex interdependencies among dimensions. Importantly, only then the links between the raw indicators, i.e. a dashboard, and the dimensional indices of multidimensional poverty can be understood and communicated for a dynamic context as well. This feature is not only of academic interest, but highly policy relevant as well. Fighting poverty involves different policy-fields and requires, moreover, their coordination. The respective relevant policy makers and their advisory teams need to know how 'their' indicators relate to multidimensional poverty—particularly for changes over time.

Second, in principle dashboard and dimensional indices of multidimensional poverty could provide similar conclusions. However, there are reasons to expect both approaches to produce different results more frequently. The evidence that poor seem to be systematically more (less) likely to enter (leave) a deprivation, for instance, implies that it is not clear to what extend a change in the uncensored headcount ratio ultimately affects the poor. Additionally, if different indicators change in different directions, this may induce complex interactions in multidimensional poverty. Even though tractable, these interactions may further increase the contrast to dashboard-based findings. There may however also be scenarios in which relying on both simultaneously allows reasonable conclusions. For other, more complex situations, a careful year-to-year analysis using panel data is inevitable.

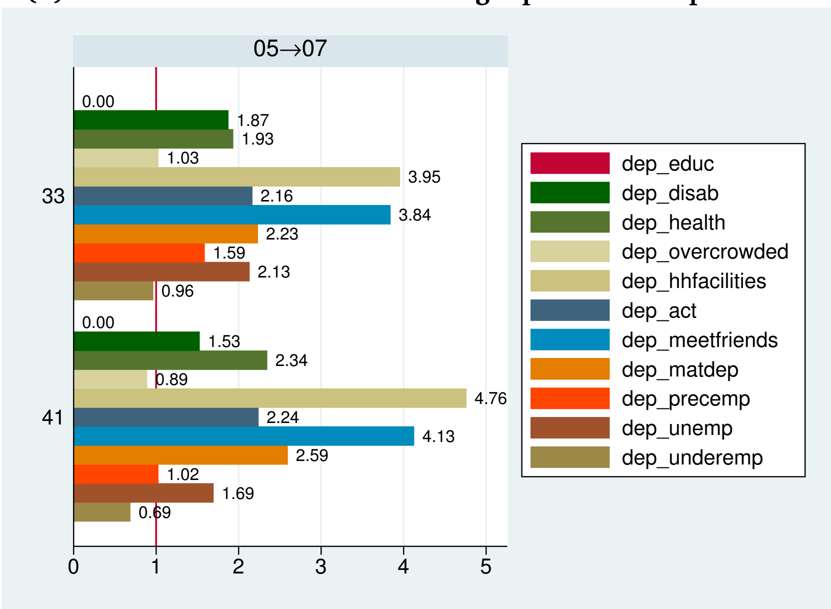
Third, in absence of panel data, there are some situations, in which neither censored nor uncensored headcount ratios, nor their simultaneous analysis can reliably reveal behavioural on-the-ground transitions of the poor. This is however vital for the evaluation of a policy measure and thus for policy incentives. Assume, for instance, that the unemployment rate fell due to the latest labour market reform, while simultaneously a large-scale health reform was implemented, which substantially reduced deprivations in health. Then a decrease in censored headcount ratio of unemployment may either reflect the success of the labour market reform (through behavioural transitions) or it may signal a success

Figure 9: Outflow and Inflow Ratios of Deprivations

(a) Outflow ratio: Odds for leaving a particular deprivation.



(b) Inflow ratio: Odds for obtaining a particular deprivation.



Notes: Data from SOEP. The odds in panel (a) are calculated as probability for leaving a deprivation of poor relative to the respective probability of the non-poor (and conditional on being deprived in that particular deprivation.

of the health reform, since due to better health less people are considered poor, despite still being unemployed (i.e. due to mechanical transitions). Hence it must remain unclear which reform was a success and whether one of them perhaps failed to reach the poor after all. The empirical relevance of issues like these naturally increases with the period between two observations. Future research may identify other scenarios in which behavioural transitions can be credibly estimated.

Fourth, as demonstrated above, changes in multidimensional poverty can be reduced to transitions in deprivations, which already offer a substantial interpretation. In some sense, however, this is an intermediate step, unique to multidimensional poverty, as transitions in deprivations demand explanation as well. Thus behavioural transitions may emerge as an adequate interface for deeper econometric analyses examining, e.g., the influence of growth, institutional and other structural changes, or specific policy measures. Note that explaining simple censored headcount ratios may be misleading, since these may also reflect transitions in other dimensions (i.e. mechanical changes). Just imagine one wanted to understand the increase in educational deprivation among the poor, observed in the empirical illustration, using conventional regression techniques.

Finally, as the continuing scarcity of panel data commands a most efficient analysis, it is noteworthy that even a two-year panel data analysis allows valuable insights. For one, such an analysis may illuminate the process of how deprivation accumulate. Specifically, an in-depth analysis of poverty exits and entries, where behavioural and mechanical transitions are distinguished already reveals at which stage a certain deprivation tends to occur or disappear, and how persistent deprivations tend to be. Additionally, even a two-year panel analysis can provide empirical evidence about the relative chances for poor and non-poor to enter or leave a deprivation, thereby facilitating more reliable conclusions based repeated cross-sectional data.

References

ALKIRE, S., APABLAZA, M., CHAKRAVARTY, S. R. and YALONETZKY, G. (2014a). *Measuring Chronic Multidimensional Poverty: A Counting Approach*. OPHI Working Paper 75, Oxford Poverty & Human Development Initiative (OPHI), Oxford.

—, BALLON, P., FOSTER, J., ROCHE, J. M., SANTOS, M. E. and SETH, S. (2015). *Multidimensional Poverty Measurement and Analysis: A Counting Approach*. Oxford Univ. Press.

— and FOSTER, J. (2011a). Counting and multidimensional poverty measurement. *Journal of Public Economics*, **95** (7-8), 476–487.

— and — (2011b). Understandings and misunderstandings of multidimensional poverty measurement. *Journal of Economic Inequality*, **9** (2), 289–314.

—, — and SANTOS, E. M. (2011). Where did identification go? *Journal of Economic Inequality*, **9** (3), 501–505.

— and FOSTER, J. E. (2016). *Dimensional and Distributional Contributions to Multidimensional Poverty*. OPHI Working Paper Series 100, Oxford Poverty and Human Development Initiative (OPHI), University of Oxford, Oxford.

— and ROBLES, G. (2016). *Measuring Multidimensional Poverty: Dashboards, Union Identification, and the Multidimensional Poverty Index (MPI)*. OPHI Research in Progress Series 46a, Oxford Poverty and Human Development Initiative, Oxford.

—, ROCHE, J. M. and VAZ, A. (2014b). *Multidimensional Poverty Dynamics: Methodology and Results for 34 Countries*. OPHI Research in Progress Paper 41a, OPHI, University of Oxford.

— and SANTOS, M. E. (2014). Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. *World Development*, **59**, 251–274.

— and SETH, S. (2015). Multidimensional poverty reduction in india between 1999 and 2006: Where and how? *World Development*, **72**, 93–108.

APABLAZA, M. and YALONETZKY, G. (2013). *Measuring the Dynamics of Multiple Deprivations among Children: The Cases of Andhra Pradesh, Ethiopia, Peru and Vietnam*. Working Paper 101, Young Lives.

ATKINSON, A. B. (2003). Multidimensional deprivation: Contrasting social welfare and counting approaches. *Journal of Economic Inequality*, **1** (1), 51–65.

BANE, M. J. and ELLWOOD, D. T. (1986). Slipping into and out of poverty: The dynamics of spells. *Journal of Human Resources*, **21** (1), 1–23.

BIGSTEN, A. and SHIMELES, A. (2008). Poverty transition and persistence in ethiopia: 1994-2004. *World Development*, **36** (9), 1559–1584.

BOSSERT, W., CHAKRAVARTY, S. R. and D'AMBROSIO, C. (2012). Poverty and time. *Journal of Economic Inequality*, **10**, 145–162.

BOURGUIGNON, F. and CHAKRAVARTY, S. (2003). The measurement of multidimensional poverty. *Journal of Economic Inequality*, **1** (1), 25–49.

CHAKRAVARTY, S. R., MUKHERJEE, D. and RANADE, R. R. (1998). On the family of subgroup and factor decomposable measures of multidimensional poverty. In D. J. Slottje (ed.), *Research on Economic*, vol. 8, Bingley: Emerald, pp. 175–194.

FERREIRA, F. H. G. and LUGO, M. A. (2013). Multidimensional poverty analysis: Looking for a middle ground. *World Bank Research Observer*, **28** (2), 220–235.

FOSTER, J., GREER, J. and THORBECKE, E. (1984). A class of decomposable poverty measures. *Econometrica*, **52** (3), 761–66.

HOY, M. and ZHENG, B. (2011). Measuring lifetime poverty. *Journal of Economic Theory*, **146**, 2544–2562.

HULME, D. and SHEPHERD, A. (2003). Conceptualizing chronic poverty. *World Development*, **31** (3), 403–423.

JALAN, J. and RAVALLION, M. (1998). Transient poverty in postreform rural china. *Journal of Comparative Economics*, **26** (2), 338–357.

— and — (2000). Is transient poverty different? evidence for rural china. *Journal of Development Studies*, **36** (6), 82–99.

LILLARD, L. A. and WILLIS, R. J. (1978). Dynamic aspects of earning mobility. *Econometrica*, **46** (5), 985–1012.

MCKAY, A. and LAWSON, D. (2003). Assessing the extent and nature of chronic poverty in low income countries: Issues and evidence. *World Development*, **31** (3), 425–439.

RAVALLION, M. (2011). On multidimensional indices of poverty. *Journal of Economic Inequality*, **9** (2), 235–248.

— (2012). Mashup indices of development. *The World Bank Research Observer*, **27** (1), 1–32.

RODGERS, J. R. and RODGERS, J. L. (1993). Chronic poverty in the united states. *Journal of Human Resources*, **28** (1), 25–54.

STEVENS, A. H. (1999). Climbing out of poverty, falling back in: Measuring the persistence of poverty over multiple spells. *Journal of Human Resources*, **34** (3), 557–588.

STIGLITZ, J. E., SEN, A. K. and FITOUSSI, J.-P. (2009). *Report by the Commission on the Measurement of Economic Performance and Social Progress*. Tech. rep., Commission on the Measurement of Economic Performance and Social Progress.

SUPPA, N. (2015). *Towards a Multidimensional Poverty Index for Germany*. OPHI Working Paper 98, University of Oxford.

TSUI, K. (2002). Multidimensional poverty indices. *Social Choice and Welfare*, **19** (1), 69–93.

WAGNER, G. G., FRICK, J. R. and SCHUPP, J. (2007). The german socio-economic panel study (soep): Scope, evolution and enhancements. *Schmollers Jahrbuch*, **127** (1), 139–169.