# Transitions in Poverty and its Deprivations.

## An Analysis of Multidimensional Poverty Dynamics

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**Abstract** This paper explores a novel way to analyse poverty dynamics that is specific to certain measures of multidimensional poverty, such as the "adjusted headcount ratio" of the Alkire-Foster class of measures. Assuming there is panel data available, I show that a simultaneous and comprehensive account of transitions in deprivations and poverty allows complex interdependencies between dimensions in a dynamic context to be handled and, at the same time, allows for several advanced types of analyses. These analyses include (i) a decomposition of changes in multidimensional poverty, which reveals *why* poverty decreases or increases; (ii) a framework to examine and understand the relationship between the dashboard approach and dimensional contributions and multidimensional poverty in a dynamic setting; (iii) a presentation of methods that illuminate the process of the accumulation of deprivations. The suggested types of analyses are illustrated using German panel data. Implications for monitoring and policy evaluation 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 recognised. 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. Nowadays, rather different methodological strategies have been devised and refined to study this and related questions. The components-of-variance approach (Lillard & Willis, 1978), the spell approach (Bane & Ellwood, 1986), and other component-based methods (Jalan & Ravallion, 1998) are frequently applied.[1] Applications cover developing and advanced economies alike and frequently employ several of the aforementioned techniques simultaneously (e.g., Stevens, 1999, Bigsten & Shimeles, 2008). In their seminal contribution, Bane & Ellwood (1986) advocate the application of hazard-type models, pointing out that these models also allow the driving factors behind poverty entries, exits and reentries (i.e. the covariates of poverty transitions) to be illuminated.[2]

Recently, substantial improvements in multidimensional poverty measurement have been achieved as well (Tsui, 2002, Bourguignon & Chakravarty, 2003, Alkire & Foster, 2011a). So far multidimensional poverty measures have mostly been applied to cross-sectional or repeated cross-sectional data (e.g. Alkire & Santos, 2014, Alkire *et al.* , 2017a, Alkire & Seth, 2015). However, there are first attempts at also exploiting panel data. Alkire *et al.* (2017b), for instance, address chronicity within multidimensional poverty, whereas Alkire *et al.* (2015, pp.273–276) suggest analyses by so-called dynamic subgroups (e.g. the ongoing poor, non-poor and those exiting or entering poverty). Finally, Apablaza & 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 that is unique to certain measures of multidimensional poverty. Specifically, multidimensional measures that satisfy dimensional breakdown offer an inherent way of exploring the driving factors behind changes in poverty, as changes can be traced back to the poverty measures' constitutive variables and interpreted accordingly. Conventional analyses, in contrast, rely on covariates external to the measure.[3] As this approach requires the dimensional breakdown and subgroup decomposability properties, I adopt the adjusted headcount ra-

[1] See also: Rodgers & Rodgers (1993), Jalan & Ravallion (2000), Hulme & Shepherd (2003), Mckay & Lawson (2003).

[2] Other 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 emphasised). Hoy & Zheng (2011), for instance, argue that poverty experiences early in the life cycle should be considered more severe; whereas Dutta *et al.* (2013) show how to account for the mitigating impact of affluent spells independent from the detrimental impact of consecutive spells in poverty.

[3] Therefore, this kind of analysis has no direct counterpart in monetary poverty analysis. The corresponding analysis in an unidimensional case appears to be trivial and unrevealing.

tio, $M_0$, a multidimensional poverty measure suggested by Alkire & Foster (2011a) which also satisfies other important axioms.[4] Apablaza & 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 their interdependencies with other dimensions. In fact, in this paper I show that their identification is feasible but requires the use of panel data. Specifically, the dimensional contribution to $M_0$ is the weighted censored headcount ratio and is generally not independent from changes in other dimensions, which may complicate the analysis substantially. Following Apablaza & Yalonetzky (2013), I reduce changes in aggregate partial indices to transitions in deprivations and poverty. However, I adopt a more comprehensive account of transitions in deprivation and poverty, which allows the complex interdependencies between dimensions to be handled and, at the same time, allows for other advanced forms of analysis. For instance, I show how genuine transitions (which drive changes in poverty) and transitions due to cross-dimensional interactions can be discriminated. This discrimination allows me to decompose changes in multidimensional poverty so that the driving factors are revealed. Thus, certain multidimensional poverty measures can inherently provide insights into *why* poverty changed. Taken by themselves, these insights can be vital for both monitoring and policy evaluation.

Another important form of analysis distinguishes between genuine transitions and cross-dimensional interactions as a way to scrutinise poverty entries and exits. Then, deprivations that were in place before entering poverty can be identified along with deprivations that remain after leaving poverty. By drawing attention to the timing of deprivations, this analysis subjects the process of *how deprivations accumulate* to critical scrutiny. A complementary analysis studies transitions into and out of deprivations, differentiated by poverty status, which also illuminates the accumulation process of deprivations. Specifically, it can be tested whether, for example, poor individuals who are not deprived in dimension $d$ are more likely to enter this deprivation than the non-poor (and non-$d$-deprived).

In addition to that, simple deprivation rates can also be reduced to different types of transitions. Importantly, this step allows dimensional changes in multidimensional poverty to be related to changes in its raw indicators, which not only provides a useful framework for an empirical analysis, but also offers a natural way to rationalise potentially inconclusive findings. A deeper understanding of these relationships is important for two reasons. First, this is of immediate importance from a policy perspective, since fighting poverty involves numerous policy sectors, such as health, education, labour, or agriculture. Consequently, different agencies and departments play a part in fighting poverty, each of which focuses on its own subset of prime indicators. However, a strongly indicator-specific perspective runs the risk of ignoring the interaction

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

between 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 be 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 simple deprivation rates 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 a consensus that poverty *is* multidimensional and that "joint distribution" is the interesting part of poverty analysis (Ferreira & 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 & Foster, 2011b), others prefer a "credible set of multiple indices" (Ravallion, 2011), and yet others suggest complementing the dashboard with a separate analysis of the joint distribution (Ferreira & Lugo, 2013). Advocates of multidimensional measures argue that exploiting the joint distribution in the identification step offers unique insights into poverty (e.g., Alkire *et al.* , 2011). However, critics of multidimensional poverty measures question the added value of dimensional decompositions (Ravallion, 2011).[5] To sum up, it is central to document and understand eventual discrepancies between a dashboard of indicators and dimensional indices of multidimensional poverty for (i) monitoring and policy evaluation and (ii) in order to assess the role of the "joint distribution" in poverty measurement and analysis. Finally, using the dual-cutoff counting approach allows also to explore the implications of a union approach to identification for the analysis of poverty dynamics. Indeed, the presented analysis highlights that poverty measures, which identify poverty only with *multiple* deprivation can provide novel insights into poverty dynamics, essentially because they focus on an important subset of the deprived population, which may be subject to different trends. Instead, poverty measures which identify an individual as poor with their first deprivation cannot reveal such patterns. This is important, as many alternative suggestions for measuring multidimensional poverty rely on union identification.[6]

The remainder of this paper is structured as follows: section 2 briefly introduces the counting approach to multidimensional poverty, section 3 outlines the suggested framework for the analysis of transitions in deprivations and poverty, section 4 presents additional methods, section 5 provides an empirical illustration and section 6 offers some concluding remarks.

[5] Further arguments around this debate can be found in Alkire *et al.* (2011), Alkire & Foster (2011b), Ravallion (2011, 2012), Alkire & Robles (2016). Major points of discussion also include the substitutability and complementarity between dimensions as well as sensitivity to inequality (e.g., Silber, 2011, Rippin, 2016).

[6] See, for instance, Datt (2013), Dotter & Klasen (2014), Rippin (2016).

## 2 Counting Approaches to Multidimensional Poverty

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

*Identification.* The matrix $y$ contains the available data, is $N \times D$ in size and describes the achievement in each dimension deemed relevant for each individual. Specifically, $y_{id} \geq 0$ represents the achievement of an 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 in order not to be considered deprived in the respective dimension). Using this information, we obtain the vector $c$ by counting weighted individual deprivations (i.e. the column vector's elements are $c_i = \sum_{d=1}^{D} w_d \mathbb{1}(y_{id} < z_d)$, where $0 \leq w_d \leq 1$ and $\sum_{d=1}^{D} w_d = 1$). Alkire & Foster (2011a)'s key idea is to define the so-called identification function as $\rho_k(y_i, z) = \mathbb{1}(c_i \geq k)$ for $k \in [0, 1]$. An individual is considered to be poor if their weighted deprivation count is larger than a critical threshold $k$, the poverty cutoff. Thus, in multidimensional poverty measurement a deprivation refers to a critically low achievement in one dimension—poverty, instead, to a critically high deprivation count.

*Aggregation.* 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 poor individuals. Following Alkire & Foster (2011a), the average deprivation among the poor (the intensity) is defined as $A = \sum_{i=1}^{N} \underline{c}_i/(q)$, where $\underline{c}_i = \mathbb{1}(c_i \geq k)c_i$ is the censored counting vector. 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 incidences and breadth of poverty. In principle, other elements of the Foster-Greer-Thorbecke (FGT) class of measures (see Foster *et al.* , 1984) can be applied as well—however, including them in the discussion is beyond the scope of this paper. Two further quantities, which are at the centre of the present analysis are the so-called censored and uncensored deprivation headcount ratios, both of which are dimension-specific. The uncensored headcount ratio, essentially the simple deprivation rate, represents the proportion of individuals deprived in a dimension $d$, and can be written as $h_d = \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}(y_{id} \leq z_d)$. The censored headcount ratio, instead, considers only persons who are deprived in dimension $d$ and who are multidimensionally poor at the same time, i.e. $\underline{h}_d = \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}(c_i \geq k \wedge y_{id} \leq z_d)$.

*Decompositions.* The adjusted headcount $M_0$ and both its individual components and its changes over time have been shown to be decomposable in numerous ways. First, since the adjusted headcount ratio fulfils a dimensional breakdown (Alkire & Foster, 2011a, 2016), it can be expressed as a weighted average of dimensional contributions (post identification) (i.e. $M_0 = \sum_{d=1}^{D} w_d \underline{h}_d$).[7] Second, as the adjusted headcount ratio also fulfils subgroup decomposability, it can be expressed as a population-weighted sum of population-specific poverty. For $l = 1, \ldots, L$ 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 at more than one point of time is available, we also can calculate and decompose changes in aggregate measures. Importantly, changes in the adjusted headcount can be decomposed into changes in dimension-specific censored headcount ratios (Apablaza & Yalonetzky, 2013). Specifically, absolute changes, denoted as $\Delta M_0$, and relative changes, denoted as $\delta M_0$, 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 $s_d^{t-1} = w_d \frac{\underline{h}_d^{t-1}}{M_0^{t-1}}$ is the contribution of dimension $d$ to the adjusted headcount ratio in the previous period. Alternatively, $\Delta M_0$ can also be decomposed into population-specific changes (Alkire *et al.* , 2015, pp.271–273) or dimensional changes by subgroups. If, moreover, panel data is available, Alkire *et al.* (2015, pp.273–276) suggest partitioning the population into dynamic subgroups (i.e. ongoing poor, poverty entries, poverty exits, and non-poor). Subgroup decomposability then allows $M_0$ to be stated 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 of the changes for the ongoing poor, increases due to entries and decreases due to exits. Subsequently, dimensional decompositions of dynamic subgroups can be analysed. The present paper argues that this analysis of dynamic subgroups is only one possibility for how to exploit the 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 the transitions of deprivation and poverty.

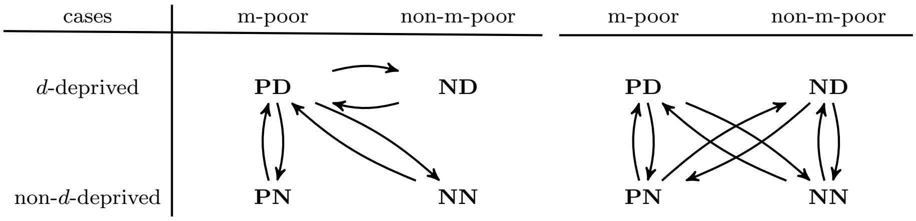
## 3 Transitions in Deprivations and Poverty

*Notation.* In order to better understand changes in multidimensional poverty several different states have to be distinguished, depending on both the 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

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

a) and the uncensored headcount ratio (panel b). For instance, the censored headcount decreases if poor people leave the deprivation but remain in poverty ($PD \to PN$), leave the deprivation and poverty ($PD \to NN$) or leave poverty but not the deprivation $d$ ($PD \to ND$).

**Fig. 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 $PD_{id}^t := c_i^t \geq k \wedge y_{id}^t < z_d$, $ND_{id}^t := c_i^t < k \wedge y_{id}^t < z_d$, $PN_{id}^t := c_i^t \geq k \wedge y_{id}^t > z_d$, and $NN_{id}^t := c_i^t < k \wedge y_{id}^t > z_d$. Moreover, we can denote the respective proportions in the population as follows: the censored headcount $\underline{h}_d^t$ is the share of the poor and deprived, whereas $h_d^t - \underline{h}_d^t$ are $d$-deprived but not poor, and $H^t - \underline{h}_d^t$ are poor but not $d$-deprived. Finally, $1 - H^t - h_d^t + \underline{h}_d^t$ 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, $PD \to PN$, can be written as the product of the respective conditional probability and the share of the $PD$ in $t-1$ (i.e. $\Pr(PN_d^t | PD_d^{t-1}) \times \underline{h}_d^{t-1}$). For notational convenience, I hereafter omit the time and dimension index within the conditional probabilities. Figure 1 substantially facilitates subsequent analysis and argumentation. First, the figure comprises virtually all transitions relevant for the present analysis, and thereby it also helps organise the different types of transitions depending on the respective objective. For instance, transitions may be grouped according to how the poverty status changes. Moreover, figure 1 also highlights that a change of a given deprivation status, may or may not entail a change in the poverty status. Finally, it also becomes visible that changes in two key quantities, the censored and the uncensored headcount ratio, in part reflect different types of transitions, which are further explored below.

*Genuine Changes and Cross-Dimensional Interactions.* Alkire *et al.* (2015, pp.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 them leaving poverty due to developments in other dimensions.[8] The present

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

framework for the analysis of transitions in poverty and deprivations allows these interdependencies among dimensions to be formulated 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:[9]

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

The first two terms in equation (2) describe transitions where the poverty status changes in line with the deprivation status, i.e. leaving this deprivation is associated with leaving poverty. As both statuses change in the *same direction*, I denote these transitions as $T_d^{\text{directional}} = \Pr(PD|NN) \times (1 - H^{t-1} - h_d^{t-1} + \underline{h}_d^{t-1}) - \Pr(NN|PD) \times \underline{h}_d^{t-1}$. The next two terms indicate transitions where the poverty status remains the same. As these transitions entirely take place *within* poverty I denote them as $T_d^{\text{within}} = \Pr(PD|PN) \times (H^{t-1} - \underline{h}_d^{t-1}) - \Pr(PN|PD) \times \underline{h}_d^{t-1})$. Furthermore, the sum of these four *genuine* transitions is denoted as $T_d^{\text{genuine}}$. In contrast, the last two terms in equation (2) describe transitions where only the poverty status changes, which can be caused by changes in other dimensions. Since these transitions arise due to an interaction of developments in other dimensions with the identification step of poverty measurement, I call this a *cross-dimensional interaction* (CDI), denoted as $T_d^{\text{CDI}} = \Pr(PD|ND) \times (h_d^{t-1} - \underline{h}_d^{t-1}) - \Pr(ND|PD) \times \underline{h}_d^{t-1}$. Changes in the censored headcount ratio can thus also be written as

$$\Delta \underline{h}_d = T_d^{\text{within}} + T_d^{\text{directional}} + T_d^{\text{CDI}}. \tag{3}$$

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

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

*Decomposing $\Delta M_0$.* As the censored headcount can be written as $\underline{h}_d = T_d^{\text{genuine}} + T_d^{\text{CDI}}$, this can be substituted into equation (1) yielding the following helpful decomposition of $M_0$:

$$\Delta M_0 = \sum w_d (T_d^{\text{genuine}} + T_d^{\text{CDI}}). \tag{5}$$

[9] Alternatively, one could also study relative changes, which can be obtained by dividing both sides of equation (2) by $\underline{h}_d^{t-1}$. However, for convenience, the subsequent argumentation uses absolute changes.

Intuitively, the decomposition in equation (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 illustrations. Alternatively, equation (3) can also be substituted into (1). Aggregating over dimensions (while accounting for weight and incidence) gives another interesting transition-based decomposition of $\Delta M_0$:

$$\Delta M_0 = \sum w_d T_d^{\text{within}} + \sum w_d T_d^{\text{directional}} + \sum w_d T_d^{\text{CDI}}. \tag{6}$$

Intuitively, equation (6) partitions changes in $M_0$ into transitions that take place entirely within poverty, directional transitions that also change the headcount ratio $H$, and transitions due to CDI that come about as a by-product of exits and entries. In some sense, equation (6) can be viewed as another incidence-intensity breakdown of $M_0$. Finally, equation (4), which organises transitions according to the associated change in the poverty status, can also be substituted into (1). Rearranging terms then gives

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

which is precisely what Alkire *et al.* (2015, p.274) suggest, based on decomposition by dynamic subgroups. Note that dimensions may or may not be distinguished in these decomposition. Moreover, as transitions are net quantities, opposing developments may cancel each other out and terms in equations (5)–(7) may have different signs.

*Remarks on Cross-Dimensional Interactions.* Five brief remarks may help in understanding the nature and relevance of CDI better. First, CDI are related to the identification step in poverty measurement and originate from the axiom of poverty focus. As soon as an individual's weighted deprivation count falls below the poverty cutoff, their remaining deprivations must be ignored. This is normatively desired since this person is, even though still deprived in some dimension, no longer poor. Second, conceptually, transitions due to CDI are simply deprivations that have already been entered into previously, not currently. Hence, a careful analysis of CDI can illuminate the accumulation processes of deprivations. Third, as CDI-based transitions result from poverty entries and exits, they become more important if entries, exits, or both become quantitatively more important. Thus, while a large $\Delta H$ indicates their relevance, a small $\Delta H$ does not preclude them. Fourth, CDI are relevant for all $k$'s except in a union approach, where individuals only leave poverty when they have left their very last deprivation. Put differently, the union approach does not allow individuals to be non-poor but $d$-deprived, which implies censored and uncensored headcounts are identical and transitions of the type $PD \leftrightarrows ND$ do not to exist.[10] Fifth, unless poverty exits are caused by simultaneous improvements in several dimensions, transitions due to CDI may well

[10] Accordingly, $M_0$ can be decomposed into the *un*censored headcounts only when using union identification (Alkire & Foster, 2011a, p.482), which implies "factor decomposability" in the way Chakravarty *et al.* (1998, p.179) use the term.

account for more than half of $\Delta M_0$ (see, e.g., section 5). Likewise, CDI tend to become more prevalent with increasing $k$'s, since people may leave poverty while "taking more deprivations with them".

*Decomposing the Uncensored Headcount.* The dashboard approach essentially studies changes indicator by indicator (i.e. uncensored headcount ratios). Decomposing the uncensored headcount into the different transitions is thus essential to explore the link between multidimensional poverty and the dashboard approach in a dynamic context.

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

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

Again, transitions can be grouped and labelled. It can be observed that changes in uncensored headcounts, like changes in censored headcounts, also reflect the transition types $T_d^{\text{within}}$ and $T_d^{\text{directional}}$, whereas $T_d^{\text{CDI}}$ are absent. Importantly, two further types of transitions can be distinguished: first, transitions in the deprivation status of the non-poor, which do not affect their poverty status (i.e. they take place entirely *outside* poverty: $T_d^{\text{outside}} = \Pr(ND|NN)\times(1-H^{t-1}-h_d^{t-1}+\underline{h}_d^{t-1})-\Pr(NN|ND)\times(h_d^{t-1}-\underline{h}_d^{t-1})$). Second, transitions in deprivations can run also counter to the change in poverty status, i.e. *counter-directional*, which are denoted as $T_d^{\text{counter}} = \Pr(PD|NN)\times(1-H^{t-1}-h_d^{t-1}+\underline{h}_d^{t-1}) - \Pr(PN|ND)\times(h_d^{t-1}-\underline{h}_d^{t-1})$). While empirically observable, these sorts of transitions may be negligible in certain scenarios. As counter-directional transitions, like CDI, are sensitive to developments in other dimensions, both may be considered to reflect 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

$$\Delta h_d = T_d^{\text{within}} + T_d^{\text{outside}} + T_d^{\text{directional}} + T_d^{\text{counter}}. \tag{9}$$

Equation (9) essentially shows that changes in single indicators may (i) only change the intensity of poverty among the poor, (ii) change in line with poverty status, (iii) not affect the poor at all or (iv) be overlaid by changes in other dimensions such that transitions in $d$ change counter to poverty status. Alternatively, the transitions involving a change in poverty status (i.e. $T_d^{\text{counter}}$

and $T_d^{\text{directional}}$) can also be regrouped such that the direction of that change is indicated (i.e. entries and exits)

$$\Delta h_d = T_d^{\text{p-entry}} + T_d^{\text{within}} + T_d^{\text{outside}} + T_d^{\text{p-exit}}. \tag{10}$$

Equation (10) may, for instance, reveal large quantities of $d$-related poverty entries and exits (e.g. due to unemployment), which may cancel each other out if only $\Delta h_d$ is studied. Both equations (9) and (10) help us to better understand how the poor are affected by, say, an overall decrease in child mortality or an increase in unemployment. Section 5 illustrates this.

*Censored and Uncensored Headcount Ratios.* Two important questions demand a greater understanding of how changes in censored and uncensored headcount ratios are related: first, whether the identification step in multidimensional poverty 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 of which transitions are reflected by each quantity and how the quantities differ according to the various transitions. Figure 1 already shows that both censored and uncensored headcounts reflect transitions of deprivations that take place within poverty ($T_d^{\text{within}}$) or change the poverty status ($T_d^{\text{directional}}$). Taking their difference, however, clearly reveals that there are several reasons for why both quantities might suggest different developments:

$$\Delta h_d - \Delta \underline{h}_d = T_d^{\text{outside}} + T_d^{\text{counter}} - T_d^{\text{CDI}}. \tag{11}$$

Equation (11) identifies three major reasons for why changes in $h_d$ and $\underline{h}_d$ may differ: first, only the uncensored headcount reflects transitions in $d$ that do not affect the poor at all or, second, those transitions that run counter to the change in the poverty status, and, third, only the censored headcount reflects changes, such as decreases, due to improvements in the other dimensions, even though no on-the-ground change in $d$ takes place. Also note that equation (11) refers to net transitions, which consequently may be positive or negative. Thus, $T_d^{\text{CDI}}$ may increase or decrease the difference and, more importantly, add to $T_d^{\text{outside}}$ or run counter to it.

If the goal is to uncover eventual genuine differences between the changes in plain indicators and how changes in dimensions affect the poor, it would be convenient to focus on "on-the-ground changes" (i.e. $T_d^{\text{genuine}}$). However, even if $T_d^{\text{CDI}}$ were irrelevant or known, equation (11) shows that different conclusions may still emerge for several reasons. First, the poor may be affected differently in a systematic way from non-poor, in the sense that, for example, $d$-deprived poor are less likely to leave deprivation $d$ than non-poor but $d$-deprived individuals (also see section 4.1). In relation to that, changes in the uncensored headcount ratio may largely reflect changes among non-poor, which also depends on the relative sizes of $H^{t-1}$, $h_d^{t-1}$, and $\underline{h}_d^{t-1}$, among other things.[11] 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 counter-directional transitions (i.e. due to more complex interdependencies among dimensions). If, for instance, a non-poor unemployed individual 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.[12]

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 the uncensored headcount ratio can offer only limited back-up for analyses with repeated cross-sectional data: Partly, because CDI complicate the analysis, partly because it remains unclear to which extent the non-poor are affected. Importantly, as policy failures may go undetected, this produces an incentive problem for policy makers. If, for instance, a widespread deprivation is successfully pushed back, the induced CDI may mask actual increases in other indicators or the inefficacy of measures taken in other policy areas. Therefore, it is important to obtain credible estimates of CDI. As, however, censored and uncensored headcount ratios may differ for several reasons identifying genuine transitions with repeated cross-sections is a non-trivial exercise which demands further research.

*Union identification.* Union identification eliminates the possibility of being deprived but not poor. This rules out the transition types $PD \leftrightarrows ND$, $ND \leftrightarrows NN$ and $ND \leftrightarrows PN$ and thereby renders the censored and uncensored headcount ratios identical (the former are in fact no longer censored). On the one hand, a union approach thus reduces the complexity of a dynamic dimension-specific analysis. On the other hand, however, the scope for novel insights is also more limited, since changes in "dimensional indices" of multidimensional poverty and simple deprivation headcount ratios will agree on how the poor are affected. Intuitively, this results from rejecting the goal of exclusively identifying *multiply* deprived people.

[11] 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).

[12] However, censored headcount ratios of housing and health would, of course, register these changes.

## 4 Related Analyses

### 4.1 Are the 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 have the same probability for entering a deprivation $d$ and, conversely, whether poor and non-poor $d$-deprived have the same probability of leaving that deprivation. These questions are interesting as multidimensional poverty measurement implicitly assumes that deprivations may accumulate under certain conditions. Answering these questions would offer some of the first descriptive evidence available 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 systematically differentiated influence. Low educational achievements in their household, for instance, may reduce the probability of a child's school attendance or finding a new job. Alternatively, the poor may also be more likely to suffer permanently from various economic shocks (which may manifest itself in asset indicators). Likewise, certain other background factors may produce such a finding. However, if introduced, a well-targeted anti-poverty policy could produce the opposite pattern, meaning that the poor are more likely to leave certain deprivations in comparison to the non-poor.

To test for such a differentiated influence one can calculate relative risks using conditional probabilities, where entering a deprivation ($RR_d^{\text{in}}$) and leaving a deprivation ($RR_d^{\text{out}}$) have to be distinguished, that is to say:

$$RR_d^{\text{out}} = \frac{\Pr(PN|PD) + \Pr(NN|PD)}{\Pr(PN|ND) + \Pr(NN|ND).} \tag{12}$$

The numerator contains the conditional probabilities of a poor and $d$-deprived individual leaving 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-poor but $d$-deprived individual. In terms of figure 1, $RR_d^{\text{out}}$ compares the transitions starting at $PD$ with those starting at $ND$. The relative risk for entering a deprivation $d$, $RR_d^{\text{in}}$, can be constructed analogously:[13]

$$RR_d^{\text{in}} = \frac{\Pr(PD|PN) + \Pr(ND|PN)}{\Pr(PD|NN) + \Pr(ND|NN).} \tag{13}$$

More importantly, if $d$-deprived are equally likely to leave a deprivation $d$, then $RR_d^{\text{out}} = 1$, whereas $RR_d^{\text{in}} = 1$ if not-$d$-deprived are equally likely to

[13] Note that these relative risks can also be obtained by appropriate logit regressions.

enter the deprivation $d$. Testing this presumption with real-world data offers important insights into the accumulation process of deprivations. Evidence on systematically different chances to leave (enter) deprivations according to poverty status would also complement the poverty cutoff with a meaningful or behavioural interpretation. Naturally, the normative nature of setting the $k$-cutoff remains unaffected. Finally, such evidence also deepens our understanding of potentially inconclusive findings of multidimensional poverty measures and dashboards on the assessment of changes over time.

### 4.2 Scrutinising Poverty Entries and Exits

Panel data allows poverty entries and exits to be studied more carefully. Assuming a two-year panel for simplicity's sake, Alkire *et al.* (2015, pp.273–276) first partition the panel into dynamic subgroups (ongoing poor, non-poor, exits and entries). As a result, dimensional decompositions can be analysed for each point in time separately or together (i.e. the change). Apablaza & 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 also allows deprivations that made an individual cross the $k$-cutoff to be distinguished from deprivations that were already entered into previously. Put differently, it is possible to distinguish between genuine transitions and those due to CDI among those who enter (or leave) poverty. Such analyses offer valuable insights into the process of how deprivations accumulate: Are there certain deprivations that frequently set the stage for entering into poverty while other deprivations make an individual finally cross over the cutoff? Which deprivations tend to be more persistent and which are not? A natural way to study these questions is to calculate the share of genuine and CDI-based transitions *into* a deprivation among those who *enter* poverty, or formally:

$$\begin{aligned}\text{p-entries}_d^{\text{genuine}} &= \frac{\Pr(PD|NN) \times (H^{t-1} - h_d^{t-1} + \underline{h}_d^{t-1})}{\Pr(c_i^t \geq k | c_i^{t-1} < k) \times (1 - H^{t-1})} \quad \text{and} \\ \text{p-entries}_d^{\text{CDI}} &= \frac{\Pr(PD|ND) \times (h_d^{t-1} - \underline{h}_d^{t-1})}{\Pr(c_i^t \geq k | c_i^{t-1} < k) \times (1 - H^{t-1})}.\end{aligned} \tag{14}$$

Likewise, the share of genuine and CDI transitions *out of* deprivations among those who *leave* poverty is calculated as

$$\begin{aligned}\text{p-exits}_d^{\text{genuine}} &= \frac{\Pr(NN|PD) \times \underline{h}_d^{t-1}}{\Pr(c_i^t < k | c_i^{t-1} \geq k) \times H^{t-1}} \quad \text{and} \\ \text{p-exits}_d^{\text{CDI}} &= \frac{\Pr(ND|PD) \times \underline{h}_d^{t-1}}{\Pr(c_i^t < k | c_i^{t-1} \geq k) \times H^{t-1}}.\end{aligned} \tag{15}$$

## 5 Evidence from Germany

*Data and Specification.* The empirical analyses in this section use data from the German Socio-Economic Panel (SOEP) (Wagner *et al.* , 2007).[14] The main purpose is to present a year-to-year analysis of multidimensional poverty using the panel data-based decompositions above. To balance competing requirements, I confine the analyses to the data waves for 2005 and 2007.[15] This allows a reasonable multidimensional poverty index and a focus on a period that is easy to manage. The specification of the multidimensional poverty index is conceptually embedded into the capability approach (e.g., Sen, 1992), follows several the recommendations of Atkinson *et al.* (2002), Stiglitz *et al.* (2009), OECD (2011), and relates to the national reports of poverty and wealth (see, e.g., Bundesregierung, 2013).[16] Table 1 summarises 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.

*Elementary Analyses.* Table 2 (a) shows levels and changes for every single indicator, and thus essentially represents the dashboard approach. Deprivation levels vary substantially ranging from approximately 1.5% (e.g. in $dep\_hhfacilities$) to more than 15% (e.g. in health, material deprivation or social activities). Whereas both housing and employment indicators decrease from 2005 to 2007, the remaining indicators all increase.[17] Specifically, the unemployment rate falls from 6.1% to 5.1%, which is approximately 1%-point in absolute terms and 20% in relative terms. While each absolute and rela-

[14] I use SOEP data v30 (DOI: 10.5684/soep.v30), provided by the DIW; see Wagner *et al.* (2007) for more details. The data used in this paper was extracted using the add-on package PanelWhiz for Stata. PanelWhiz (http://www.panelwhiz.eu) was written by John P. Haisken-DeNew (john@PanelWhiz.eu). See Haisken-DeNew & Hahn (2010) for details. The PanelWhiz-generated DO file to retrieve the data used here is available from me upon request. Any data or computational errors in this paper are my own.

[15] More specifically, most indicators are collected only every other year or less frequently, so a comprehensive multidimensional poverty index can only be compiled for a few selected years. Increasing the time period between these years, however, compounds the issue of panel attrition, which may be detrimental to the present analysis, as it requires a balanced panel. Moreover, analysing several year-to-year changes, would involve in fact several different (longitudinal) populations, which renders a careful analysis less comprehensible. As the objective of the empirical part of this paper is to illustrate the different forms of analyses, focusing on one specific year-to-year change, seems appropriate.

[16] See, e.g, Rippin (2016), Suppa (2017) for alternative specifications and complementary justifications.

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

**Table 1** Specification of the Multidimensional Poverty Index.

| Functioning | Deprivation cutoff | Variable | Weight |
|---|---|---|---|
| **Education** | left school without graduating or graduated but has no vocational qualifications[a] | dep_educ | 1/6 |
| **Housing** | bath, kitchen, water, or toilet is missing<br>less than 1 room per person in household | dep_hhfacilities<br>dep_overcrowded | 1/12<br>1/12 |
| **Health** | partially or severely disabled<br>respondent reports their health to be *poor* or *bad* | dep_disability<br>dep_health | 1/12<br>1/12 |
| **Precarity** | reporting 2/4 goods missing for financial reasons[b]<br>precariously employed (incl. temporary work) | dep_matdep<br>dep_precemp | 1/12<br>1/12 |
| **Social Participation** | at least 5/7 activities are performed *never*; remaining at most *less than monthly*[c]<br>respondent reports *never* meeting their friends | dep_actindex<br>dep_meetfriends | 1/12<br>1/12 |
| **Employment** | registered unemployed<br>working less than 30 hours a week, but desires to work more | dep_unemp<br>dep_underemp | 1/6<br>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, theatre, lectures), (iii) doing sports yourself, (iv) volunteer work, (v) attending religious events, (vi) helping out friends, relatives or neighbours and (vii) involvement in a citizens' group, political party or local government. Note that the maximum deprivation is 1.0 (despite the larger sum of all weights), since a person cannot be simultaneously unemployed and underemployed.

tive change emphasises the different aspects of the 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, for two different values of $k$. For instance, using a poverty cutoff of $k = 33\%$ approximately 10.0% were poor in 2005 and 10.8% in 2007 (i.e. the poverty headcount increased by 0.8 percentage 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 poverty is increasing independent of $k$. Levels of censored headcounts ratios are substantially smaller than levels of uncensored headcounts, implying that a substantial part of the deprivations (which would matter for a dashboard approach) are deliberately ignored once the focus is on the poor, i.e. the multiply deprived. For instance, while approximately 15% are deprived in education according to the uncensored headcount ratio, only 7% are deprived in education according to the censored headcount ratio. Moreover, the signs of changes in censored and uncensored headcounts do not necessarily match (e.g., for the housing indicators and underemploy-

**Table 2** Indicators, Indices and Contributions of Multidimensional Poverty

**(a) Dashboard**

| | 2005 | 2007 | $\Delta$ | $\delta$ |
|---|---|---|---|---|
| dep_educ | 0.1492 | 0.1499 | 0.0007 | 0.0045 |
| dep_disability | 0.1353 | 0.1488 | 0.0135 | 0.0998 |
| dep_health | 0.1909 | 0.2097 | 0.0188 | 0.0985 |
| dep_overcrowded | 0.0606 | 0.0539 | −0.0067 | −0.1101 |
| dep_hhfacilities | 0.0156 | 0.0151 | −0.0005 | −0.0308 |
| dep_unemp | 0.0614 | 0.0514 | −0.0099 | −0.1621 |
| dep_underemp | 0.0966 | 0.0930 | −0.0035 | −0.0367 |
| dep_precemp | 0.0595 | 0.0626 | 0.0031 | 0.0513 |
| dep_matdep | 0.1746 | 0.1894 | 0.0148 | 0.0848 |
| dep_act | 0.1940 | 0.2147 | 0.0207 | 0.1066 |
| dep_meetfriends | 0.0255 | 0.0313 | 0.0058 | 0.2287 |

**(b) Aggregate Indices of Multidimensional Poverty**

| | 2005 | | 2007 | | $\Delta$ | | $\delta$ | |
|---|---|---|---|---|---|---|---|---|
| $k$ | 33% | 41% | 33% | 41% | 33% | 41% | 33% | 41% |
| $M_0$ | 0.0391 | 0.0208 | 0.0424 | 0.0235 | 0.0032 | 0.0027 | 0.0828 | 0.1295 |
| $H$ | 0.1002 | 0.0454 | 0.1078 | 0.0514 | 0.0076 | 0.0059 | 0.0755 | 0.1308 |
| $A$ | 0.3902 | 0.4589 | 0.3929 | 0.4583 | 0.0027 | −0.0005 | 0.0068 | −0.0012 |
| 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 SOEPv30. Panel (a) shows uncensored headcount ratios, whereas the lower part of panel (b) shows censored headcount ratios.

ment). Additionally, some of the changes differ quantitatively and thus seem to tell different stories. Deprivation in education for instance increases 0.067 percentage points in the total population, which is rather low compared to other indicators, whereas the share of education-deprived poor increases by 0.57 percentage points, which is not only larger by a factor of 8, but also a considerable change compared to other indicators. Thus far, censored and uncensored headcount ratios offer rather inconclusive findings, thereby preventing a more meaningful interpretation of the underlying developments. The suggested panel data-based decompositions, however, allow the causes of these observations to be examined.

*Selected Decompositions.* Table 3 shows the results for selected decompositions, which prove useful in understanding the dynamics behind these first observations better. Panel (a) contains two decompositions of the censored headcount ratios and allows four instructive observations. First, the increase in the censored headcount of *dep_educ* (and *dep_precemp* as well) is entirely due to CDI. Second, in some cases CDI add to genuine changes (i.e. they change the censored headcount ratio in the same direction, for example, for disability or health), while in other cases CDI run counter to genuine changes. In fact, for *dep_overcrowded* and *dep_underemp* the CDI overlay genuine improvements in these indicators and produce an overall increase in the censored headcounts of these deprivations. Even though they are quantitatively small, these observations illustrate potential complexities that may emerge in the course of an analysis. Third, the increase in deprivation of household facilities is almost entirely due to genuine transitions, which is, in stark contrast to what a dashboard would suggest, namely unambiguously a relief in this indicator. A dimensional analysis of changes in multidimensional poverty, may thus also provide qualitatively different findings. Fourth, the other decomposition, using equation (3), distinguishes genuine transitions according to whether the poverty status changed (directional) or whether an individual remains poor (within). Leaving unemployment, for instance, was frequently accompanied by leaving poverty entirely, but not always. Some people, however, left poverty while 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.

Panel (b) of table 3 shows two decompositions of $\Delta M_0$, based on equations (6) and (7). It turns out that the slight increase for the period under investigation results mostly from net entries into poverty, partly due to new deprivations (directional) and partly due to prior deprivations (CDI). Net changes among the poor apparently contribute little. The other decomposition in panel (b) reveals that the rather modest net increase in $M_0$ comprises high numbers of entries into and exits out of poverty, which, however, offset each other. An analysis ignoring this point would most certainly be considered incomplete.

Finally, panel (c) 3 contains two possible decompositions of the uncensored headcount ratio. The upper one, using equation (9), shows that much of the indicator-specific transitions affect the non-poor (outside).[18] The results also show that counter-directional transitions sometimes do matter (e.g., in *dep_precemp*), as people become deprived due to starting work under precarious conditions while 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 addition, also increase the number of poor people. The reduction in unemployment, however, largely improved the lives of the non-poor while also improving the situation of some multiply deprived though still poor and, finally, allowing yet others to leave poverty entirely. This analysis also reflects the more complex situations of transitions relating to $dep\_hhfacilities$ and *dep_underemp*. In fact, the decomposition for deprivation in household facilities reveals, that largely non-poor individuals experienced the improvements, whereas it also points to the deterioration of the housing situation for the poor. Thus, the present analysis uncovers a potential demand for action for the housing ministry, which otherwise would go undetected, since the simple dashboard

[18] Note that this proportion of outside-poverty transitions in deprivations tends to increase with $k$.

**Table 3** Results for Selected Decompositions

**(a) Changes of censored headcount ratios**

| | | | | eq. (3) | | |
|---|---|---|---|---|---|---|
| | $\Delta \underline{h}_d$ | genuine | CDI | directional | within | CDI |
| dep_educ | 0.0057 | 0.0004 | 0.0053 | 0.0004 | 0.0000 | 0.0053 |
| dep_disability | 0.0058 | 0.0045 | 0.0012 | 0.0028 | 0.0017 | 0.0012 |
| dep_health | 0.0075 | 0.0065 | 0.0010 | 0.0046 | 0.0019 | 0.0010 |
| dep_overcrowded | 0.0026 | −0.0005 | 0.0032 | −0.0001 | −0.0004 | 0.0032 |
| dep_hhfacilities | 0.0022 | 0.0021 | 0.0001 | 0.0012 | 0.0009 | 0.0001 |
| dep_underemp | 0.0004 | −0.0013 | 0.0017 | 0.0008 | −0.0021 | 0.0017 |
| dep_unemp | −0.0044 | −0.0037 | −0.0007 | −0.0022 | −0.0015 | −0.0007 |
| dep_act | 0.0091 | 0.0089 | 0.0002 | 0.0058 | 0.0031 | 0.0002 |
| dep_meetfriends | 0.0029 | 0.0027 | 0.0002 | 0.0018 | 0.0009 | 0.0002 |
| dep_matdep | 0.0043 | 0.0038 | 0.0006 | 0.0031 | 0.0006 | 0.0006 |
| dep_precemp | 0.0015 | 0.0000 | 0.0015 | 0.0005 | −0.0006 | 0.0015 |

**(b) Change of adjusted headcount ratio**

| | | eq. (6) | | | eq. (7) | | |
|---|---|---|---|---|---|---|---|
| | $\Delta M_0$ | directional | within | CDI | p-entry | p-exit | within |
| k=33% | 0.0032 | 0.0014 | 0.0003 | 0.0016 | 0.0163 | −0.0134 | 0.0003 |
| k=41% | 0.0027 | 0.0014 | 0.0000 | 0.0014 | 0.0110 | −0.0083 | 0.0000 |

**(c) Changes of uncensored headcount ratios**

| | | eq. (9) | | | |
|---|---|---|---|---|---|
| | $\Delta h_d$ | directional | counter | within | outside |
| dep_educ | 0.0007 | 0.0004 | −0.0001 | 0.0000 | 0.0004 |
| dep_disability | 0.0135 | 0.0028 | 0.0006 | 0.0017 | 0.0084 |
| dep_health | 0.0188 | 0.0046 | 0.0002 | 0.0019 | 0.0121 |
| dep_overcrowded | −0.0067 | −0.0001 | 0.0002 | −0.0004 | −0.0063 |
| dep_hhfacilities | −0.0005 | 0.0012 | 0.0007 | 0.0009 | −0.0033 |
| dep_underemp | −0.0035 | 0.0008 | −0.0005 | −0.0021 | −0.0018 |
| dep_unemp | −0.0099 | −0.0022 | −0.0005 | −0.0015 | −0.0057 |
| dep_act | 0.0207 | 0.0058 | 0.0007 | 0.0031 | 0.0111 |
| dep_meetfriends | 0.0058 | 0.0018 | 0.0004 | 0.0009 | 0.0027 |
| dep_matdep | 0.0148 | 0.0031 | −0.0001 | 0.0006 | 0.0111 |
| dep_precemp | 0.0031 | 0.0005 | 0.0019 | −0.0006 | 0.0012 |

| | | eq.(10) | | | |
|---|---|---|---|---|---|
| | $\Delta h_d$ | within | p-exit | p-entry | outside |
| dep_educ | 0.0007 | 0.0000 | −0.0014 | 0.0017 | 0.0004 |
| dep_disability | 0.0135 | 0.0017 | −0.0014 | 0.0048 | 0.0084 |
| dep_health | 0.0188 | 0.0019 | −0.0101 | 0.0148 | 0.0121 |
| dep_overcrowded | −0.0067 | −0.0004 | −0.0027 | 0.0027 | −0.0063 |
| dep_hhfacilities | −0.0005 | 0.0009 | −0.0005 | 0.0023 | −0.0033 |
| dep_underemp | −0.0035 | −0.0021 | −0.0035 | 0.0038 | −0.0018 |
| dep_unemp | −0.0099 | −0.0015 | −0.0119 | 0.0092 | −0.0057 |
| dep_act | 0.0207 | 0.0031 | −0.0092 | 0.0157 | 0.0111 |
| dep_meetfriends | 0.0058 | 0.0009 | −0.0039 | 0.0061 | 0.0027 |
| dep_matdep | 0.0148 | 0.0006 | −0.0098 | 0.0129 | 0.0111 |
| dep_precemp | 0.0031 | −0.0006 | −0.0024 | 0.0048 | 0.0012 |

**Notes:** Data from SOEPv30. Underlying poverty cutoff in panels (a),(c) is $k = 33\%$. Units in all panels are absolute changes. The censored headcount ratio of *dep_act*, for instances, increases by 0.91 percentage points.

indicator, in fact, suggests an improvement. The other decomposition, using equation (10), distinguishes entries and exits and, therefore, reveals 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 percentage point increase of the unemployment rate. Thus, a considerable amount of people enter unemployment and poverty despite the net improvement.

*Related Analyses.* Table 4 provides a more in-depth analysis of poverty entries and exits and relative risks for deprivation entries and exits. Specifically, the first two columns contain the shares of genuine and CDI-based transitions into deprivations experienced by those entering poverty, whereas the next two columns show the shares of transitions out of deprivations for those leaving poverty. For instance, 46% of all individuals who entered poverty were already deprived in education in the first place, while 23% of those who became poor, also entered unemployment. Note that even percentages of genuine transitions add up to more than 100%; in fact, the total is approximately 180%, since many individuals enter several deprivations simultaneously. Broadly speaking, three different patterns stand out. First, some deprivations, like education and disability, appear to only matter indirectly for both entries and exits in the sense that they increase the counting vector in the first place, while the other deprivations shift the deprivation count above the $k$-cutoff. Likewise, few people leave poverty because of leaving the 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 into 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. For example, 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 a 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 deprivations—at times they are setting the stage and 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, which is intuitive and consistent with previous research. This analysis, however, additionally suggests these deprivation to have a specific role in the process of accumulating deprivations over time.

Finally, the last two columns of table 4 contain the relative risk rates for entering and leaving a certain deprivation. For several indicators, the results indicate that the relative risks for leaving a given deprivation ($RR_d^{\text{out}}$) are significantly smaller than 1, meaning that the poor are less likely to leave a deprivation. For instance, the poor are, only approximately half as likely as non-poor to leave a deprivation in education. On the other hand, table 4 also

**Table 4** Results for Related Analyses

| | p-entries | | p-exits | | | |
|---|---|---|---|---|---|---|
| | genuine | CDI | genuine | CDI | $RR_d^{\text{in}}$ | $RR_d^{\text{out}}$ |
| dep_educ | 0.04 | 0.46 | −0.04 | −0.41 | 0.00<br>(0.00 ; 0.00) | 0.54<br>(0.07 ; 1.02) |
| dep_disability | 0.11 | 0.20 | −0.05 | −0.20 | 1.87<br>(1.13 ; 2.62) | 0.92<br>(0.58 ; 1.26) |
| dep_health | 0.35 | 0.22 | −0.29 | −0.24 | 1.93<br>(1.44 ; 2.43) | 0.73<br>(0.61 ; 0.85) |
| dep_overcrowded | 0.07 | 0.12 | −0.09 | −0.06 | 1.03<br>(0.41 ; 1.64) | 0.74<br>(0.52 ; 0.96) |
| dep_hhfacilities | 0.05 | 0.01 | −0.03 | 0.00 | 3.95<br>(1.39 ; 6.52) | 0.88<br>(0.58 ; 1.18) |
| dep_act | 0.14 | 0.06 | −0.15 | −0.03 | 2.16<br>(1.68 ; 2.64) | 0.68<br>(0.56 ; 0.80) |
| dep_meetfriends | 0.23 | 0.06 | −0.33 | −0.09 | 3.84<br>(2.60 ; 5.08) | 0.91<br>(0.76 ; 1.07) |
| dep_matdep | 0.37 | 0.20 | −0.29 | −0.23 | 2.23<br>(1.67 ; 2.79) | 0.71<br>(0.59 ; 0.83) |
| dep_precemp | 0.14 | 0.02 | −0.12 | −0.02 | 1.59<br>(0.98 ; 2.19) | 1.26<br>(1.04 ; 1.48) |
| dep_unemp | 0.31 | 0.29 | −0.29 | −0.33 | 2.13<br>(1.26 ; 3.00) | 0.82<br>(0.69 ; 0.95) |
| dep_underemp | 0.12 | 0.05 | −0.13 | −0.02 | 0.96<br>(0.63 ; 1.29) | 1.20<br>(1.02 ; 1.38) |

**Notes:** Data from SOEPv30. Cells contain shares of genuine and CDI deprivation entries (exits) among poverty entries (exits) and relative risk ratios. Confidence intervals in parentheses are at 95%-level. Underlying poverty cutoff is $k = 33\%$.

reveals the poor to be more likely than non-poor to enter another deprivation since most relative risks ($RR_d^{\text{in}}$) are larger than 1 and, in fact, for several indicators they are twice as large or more. Note, however, that even though this pattern seems to be systematic, it is purely descriptive and demands further theoretical explanation. Finding a good job, for instance, may be easier for healthy and educated individuals who have effective social networks. Conversely, 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

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 enables the analyst to handle potentially complex interdependencies among dimensions. More importantly, the links between a dashboard of indicators and the dimensional indices of multidimensional poverty can be understood and easily explained in a dynamic context as well. This feature is also highly policy relevant. Fighting poverty involves different policy fields and requires their coordination. The respective policy makers and their advisory teams need to know how "their" indicators relate to multidimensional poverty—particularly for changes over time.

In principle, dashboards and dimensional indices of multidimensional poverty could provide similar conclusions. However, there are reasons to expect both approaches will produce different results more frequently. The evidence that the poor seem to be systematically more likely to enter and less likely to leave a deprivation, for instance, implies that it is not clear to what extent a change in the simple deprivation rate ultimately affects the poor. Additionally, if different indicators change in different directions, this may lead to complex interactions in multidimensional poverty. Being traceable, these interactions may further increase the contrast to dashboard-based findings.

The identification of genuine transitions based on repeated cross-sections is a non-trivial exercise, which is, however, vital for the evaluation of policy measures 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 that substantially reduced deprivations in health. Then a decrease in the censored headcount ratio of unemployment may either reflect the success of the labour market reform or it may signal a success of the health reform since, due to improved health, less people are considered poor despite still being unemployed. Hence, it remains unclear which reform was a success and whether one of them perhaps failed to reach the poor after all. The empirical relevance of such issues naturally increases with the period of time between two observations. Future research may reveal conditions under which genuine transitions can be credibly estimated.

As demonstrated above, changes in multidimensional poverty can be reduced to transitions in deprivations, which already offer a meaningful interpretation. In some sense, however, this is an intermediate step, unique to multidimensional poverty, as transitions in deprivations demand an explanation as well. Thus, genuine transitions may emerge as an adequate interface for deeper econometric analyses examining, for example, the influence of growth, institutional and other structural changes, or specific policy measures. Explaining simple censored headcount ratios, instead, is misleading, as these also reflect transitions in other dimensions.

Finally, as panel data sets continue to be rare, a careful analysis of the existing ones is called for. Thus, it is noteworthy that even a two-year panel data analysis already allows valuable insights to be gleaned, in particular into the process of how deprivations accumulate. Both the suggested in-depth analysis of poverty entries and exits, and the relative risk estimation for deprivation entries and exits are instructive and yet straightforward to apply.

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