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Transitions in Poverty and Deprivations: An Analysis of Multidimensional Poverty Dynamics

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Abstract
This paper explores a novel way to analyse poverty dynamics that are specific to certain measures of multidimensional poverty, such as the "adjusted headcount ratio" proposed by Alkire and Foster (2011a). 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. The implications for monitoring, policy evaluation and strategies for analyses using repeated cross-sectional data are discussed.

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

JEL classification: I32, C33

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The Oxford Poverty and Human Development Initiative (OPHI) is a research centre within the Oxford Department of International Development, Queen Elizabeth House, at the University of Oxford. Led by Sabina Alkire, OPHI aspires to build and advance a more systematic methodological and economic framework for reducing multidimensional poverty, grounded in people's experiences and values.

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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.* , 2015a, Alkire & Seth, 2015). However, there are first attempts at also exploiting panel data. Alkire *et al.* (2014), for instance, address chronicity within multidimensional poverty, whereas Alkire *et al.* (2015b, 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, which is included in 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 are unique to certain measures of multidimensional poverty. As this approach requires the dimensional breakdown and subgroup decomposability properties, I adopt the adjusted headcount ratio, M_0, suggested by Alkire & Foster (2011a) as a measure for multidimensional poverty that also satisfies other important axioms.[3] The idea is that multidimensional measures

[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.

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

that satisfy dimensional breakdown offer an inherent way of exploring the driving factors behind changes in poverty. 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.* , 2015b, 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 behavioural transitions (which drive changes in poverty) and mechanical transitions (which are due to interdependence) 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. As the previous analysis requires the use of panel data, which many countries still lack, I also explore under what conditions repeated cross-sectional data may provide equivalent insights. Taken by themselves, these insights can be vital for both monitoring and policy evaluation.

Another important form of analysis distinguishes between behavioural and mechanical transitions 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 further instructive descriptive analysis follows that explores when 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, 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, the same techniques can be applied to the raw or uncensored headcount ratio for each single indicator. Most 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 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 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 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 "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 (e.g., Alkire *et al.* , 2011) highlight that exploiting joint distribution in the identification phase offers unique insights into poverty (i.e. the actual identification of the poor, in comparison to the simple dashboard approach). However, critics of multidimensional poverty measures question the added value of dimensional decompositions (Ravallion, 2011).[4] To sum up, it is central to document and understand eventual discrepancies for monitoring and policy evaluation in order to assess the role of "joint distribution" in poverty measurement and analysis. Finally, it is noteworthy that using the dual-cutoff counting approach also allows the implications of choosing a union approach to identification, within the presented framework, to be explored. This is important, as many alternative suggestions for measuring multidimensional poverty rely on union identification.[5]

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,

[4]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).

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

section 5 provides an empirical illustration and section 6 offers some concluding remarks.

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.* (2015b) provide a more comprehensive discussion.

Identification and Aggregation. 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 to not be considered 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 $c_i = \sum_{d=1}^{D} w_d \mathbb{1}(y_{id} < z_d)$, 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 $k \in [1, D]$. An individual is considered to be poor if their 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 poor individuals. Following Alkire & Foster (2011a), the average deprivation among the poor (the intensity) is defined as $A = \sum_{i=1}^{N} \underline{c}_i/(qD)$, where $\underline{c}_i = \mathbb{1}(c_i \geq k)c_i$. 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 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.

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. 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 ratio. 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. $M_0 = \sum_{d=1}^{D} w_d \underline{h}_d$).[6] 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 M_0 to unfold 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. Most 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 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.* , 2015b, pp.271–273) or dimensional changes by subgroups. If, moreover, panel data is available, Alkire *et al.* (2015b, pp.273–276) suggest partitioning the population into dynamic subgroups. 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.

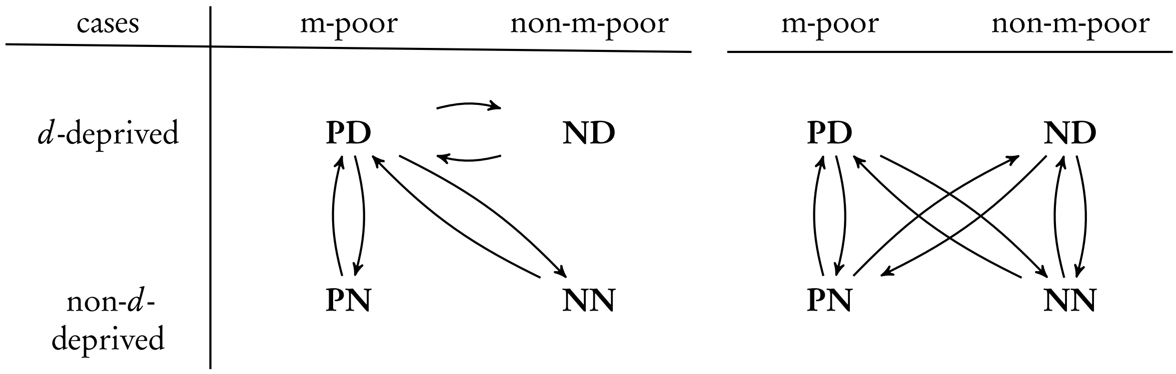
3 Transitions in Deprivations and Poverty

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 transi-

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

tions (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 in poverty ($PD \rightarrow PN$), leave the deprivation and poverty ($PD \rightarrow NN$) or leave poverty but not the 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 the time and dimension index within the conditional probabilities. Figure 1 substantially facilitates subsequent analysis and argumentation, since it helps organise the different types of transitions relevant for the respective objective. For instance, transitions may be grouped according to poverty or deprivation inflow or outflow.

Behavioural and Mechanical Changes. Alkire *et al.* (2015b, 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.[7] The present framework for the analysis of transitions in poverty and deprivations

[7]Note that censored headcount ratios are independent of achievements in other dimensions, once identification

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:[8]

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

The first two terms in equation (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 $T_d^{mec} = P(PD|ND) \times (h_d^{t-1} - \underline{h}_d^{t-1}) - P(ND|PD) \times \underline{h}_d^{t-1}$, since they represent *mechanical* changes in $\Delta \underline{h}_d$.[9] 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. $T_d^{det} = P(PD|NN) \times (1 - H^{t-1} - h_d^{t-1} + \underline{h}_d^{t-1}) - P(NN|PD) \times \underline{h}_d^{t-1}$), which is shown by 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 grouped along the associated change in 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 poverty status are T_d^{wit}). Thus, the change in the censored headcount can also be expressed as

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

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.

[8] 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.

[9] Note that mechanical changes in some dimensions d are not entirely mechanical in the sense that they are only produced by the method or the researcher. Instead, they are a 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 equation (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 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 graphical illustrations of this. 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 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, equation (6) partitions changes in M_0 into transitions that take place entirely within poverty (term 1), behavioural transitions that also change the headcount ratio H (term 2) and mechanical transitions 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 (7), which organises transitions according to the associated change in the poverty status, can also be substituted into (1). Rearranging terms then gives

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

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

Remarks on Mechanical Changes. Five brief remarks may help in understanding the nature and relevance of mechanical changes better. First, mechanical changes are related to the identification phase 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, mechanical transitions are simply deprivations that have already been entered into previously. Hence, a careful analysis of mechanical transitions can illuminate the accumulation processes of deprivations. Third, as mechanical changes in dimensions result from poverty entries and exits, they become more important if the entries, 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's except in a union approach, where an individual only leaves poverty when they have left their very last deprivation. Put differently, the union approach 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, mechanical changes may well account for more than half of ΔM_0. Likewise, mechanical changes tend to become more prevalent with increasing k's, 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 in order to better understand the link between multi-dimensional 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 a measure taken to deal with child mortality also affects the poor.

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:

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

Again, transitions can be grouped and labelled. It can be observed that changes in uncensored headcounts, like changes in censored headcounts, also reflect the transition types T_d^{wit} and T_d^{det}, whereas T_d^{mec} is 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: $T_d^{out} = P(ND|NN)\times(1-H^{t-1}-$

[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.

$h_d^{t-1} + \underline{h}_d^{t-1}) - P(NN|ND) \times (h_d^{t-1} - \underline{h}_d^{t-1})$), and, second, transitions in deprivations that run counter to the change in 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, these sorts of transitions may be negligible in certain scenarios. As dominated transitions, like mechanical transitions, rely on 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

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

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

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

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 Δh_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. The dashboard approach studies changes indicator by indicator (i.e. uncensored headcount ratios). Changes in multidimensional poverty are often decomposed into dimensional changes in order to better understand why exactly multidimensional poverty has changed. There are two important questions that demand a greater understanding of how changes in censored and uncensored headcount ratios are related: first, whether the identification phase 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 of which transitions are reflected by each quantity and how the quantities differ according to the various transitions. Figure 1 and equations (3) and (9) clearly reveal that both censored and uncensored headcounts reflect transitions of deprivations that either take place within poverty (T_d^{wit}) or change the poverty status (T_d^{det}). Taking their difference, however, clearly reveals that there are several reasons for why both quantities might suggest different developments:

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

Equation (11) identifies three major reasons for why 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 are dominated by changes in other dimensions, 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^{mec} may increase or decrease the difference and, more 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 would be convenient to focus on "on-the-ground changes" (i.e. T_d^{beh}). However, even if T_d^{mec} is ignored, 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 dominated 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

[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).

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. 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 decreasing several 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 due to the improvements in the other dimensions (i.e. due to mechanical changes). Even increases in health deprivation may be overlaid 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 are summarised in 4.3.

Union identification. As already explained above, 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.

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,

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

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 construct odds ratios using conditional probabilities, where deprivation inflow and outflow have to be distinguished, that is to say:

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

The numerator contains the conditional probabilities of a poor and d-deprived individual 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, 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:

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

More importantly, if d-deprived are equally likely to leave a deprivation d, then $r_d^{out} = 1$, whereas $r_d^{in} = 1$ if not-d-deprived are equally likely to enter the deprivation d. Testing this presumption with real-world data is an important exercise as it facilitates the analysis with repeated cross-sectional data (see section 4.3). 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.* (2015b, 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 behavioural and mechanical transitions 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 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 add up to more than 100%, as crossing the poverty cutoff may be caused by one or several deprivations. Section 5 illustrates this.

4.3 Analysing changes using cross-sectional data

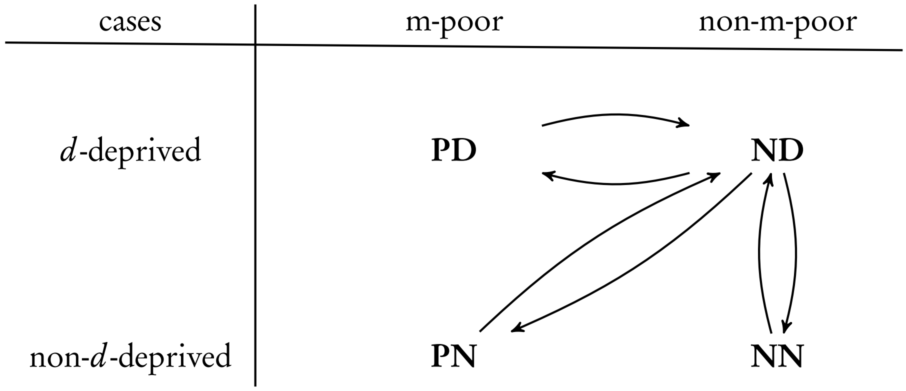
In practice, however, panel data is often still lacking. Thus, the question of how to study dimensional dynamics in multidimensional poverty using repeated cross-sectional data arises. As explained before, censored and uncensored headcount ratios each offer only a limited insight into the dimensional changes that really affect the lives of the poor. A natural way around this may be to rely on both quantities simultaneously, which raises the question about what can be inferred about behavioural transitions or on-the-ground changes from comparing censored and uncensored headcount ratios. The difference between uncensored and censored headcount ratios in equation (11), however, reveals that both quantities may differ for various reasons. Specifically, changes in d may only affect non-poor or developments in other dimensions may change poverty status, thereby producing mechanical transitions. Note that even a simultaneous decrease in both censored and uncensored headcount ratios of a dimension does not imply that a poor individual's 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 the poor and non-poor. An individual may also leave poverty entirely, although still be 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 the censored headcount of unemployment is solely due to mechanical transitions, induced by the successful health reform.

The difference between uncensored and censored headcounts can be expressed in transitions like in equation (11) and also in terms of transition probabilities:

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

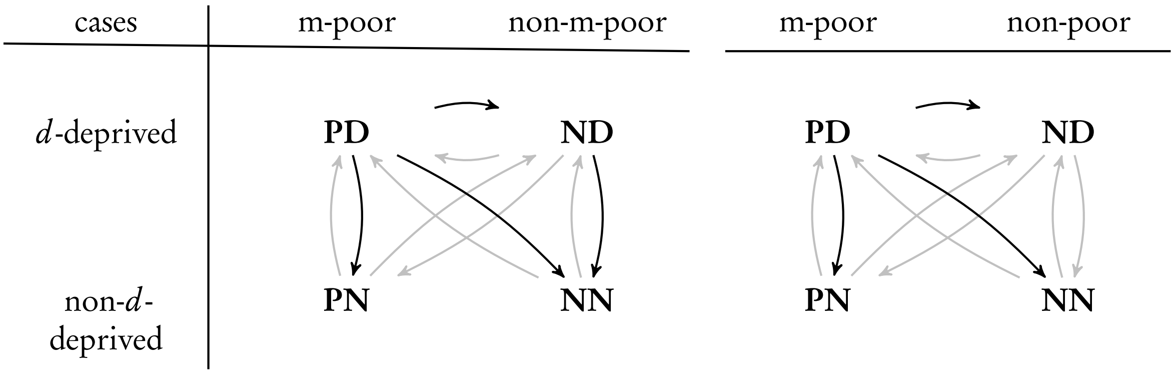
or graphically, as shown in figure 2. Both figure 2 and equation (16) suggest that without additional information, we cannot infer much by comparing uncensored and censored headcount ratios. The reasons are (i) that the difference is shaped by three different types of transitions and (ii) that each of 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



Scenario A. To illustrate how such a scenario-based inference may work, two example 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.* (2015a)). To simplify further, assume that there are no entries into deprivations, which is counter to the overall decreasing trend. Then, from all the relevant transitions that 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 the following assumptions: specifically, nobody enters a deprivation ($\rightarrow PD, \rightarrow ND$), dominated changes cannot also occur ($PN \leftrightarrows ND$) as all indicators change in the same direction, and an individual entering

Figure 3: Scenarios



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

into poverty due to changes in other deprivations (i.e. $ND \rightarrow PD$) cannot occur. Applying these assumptions to equation 16, solving for the mechanical transitions and using the definition of r_d^{out} gives

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

Recall that r_d^{out} describes the probability of leaving a deprivation for the poor relative to the probability for the non-poor. Assuming for now that there is no difference in exiting a deprivation (i.e. $r_d^{out} = 1$), this reduces our estimate to

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

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. By obtaining $T_d^{mec} < 0$, it 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 not 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 to that trend, we are left with three types of transitions. Applying the assumption to equation 16 gives (see also figure 3)

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

Intuitively, any change in the uncensored headcount must be reflected in the censored headcount as well. 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 use data from the German Socio-Economic Panel (SOEP) (Wagner *et al.*, 2007). 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 (e.g. availability of indicators and 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 a period that is easy to manage. Note, however, that Suppa (2015) suggests a more comprehensive specification for Germany (along with a more detailed justification). In any case, the present specification also serves the intended purpose. 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.

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	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 their 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 reports *never* meeting their friends	dep_meetfriends	1/12
Employment	registered unemployed	dep_unemp	1/6
	working less than 30 hours a week, but desires 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 and (vii) involvement in a citizens' group, political party or local government.

Elementary Analyses. Table 2 (a) shows levels and changes for every single indicator. A dashboard approach analysis would exclusively rely on information such as this. 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). Moreover, Table 2 also contains the changes of the deprivation indicators over time (absolute and relative), showing both housing indicators ($dep\_overcrowded$ and $dep\_hhfacilities$) and unemployment and underemployment decrease from 2005 to 2007. The remaining indicators all increase.[13] Specifically, the unemployment rate falls from 6.1% to 5.1%, which is approximately 1%-point in absolute terms and approximately 20% in relative terms. While each absolute and relative 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 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 approximately 15% are deprived in education according to the uncensored headcount ratio, only 7% are deprived in education according to the censored headcount ratio. Second, observe that the signs of changes in censored and uncensored headcounts do not necessarily match (e.g. $dep\_hhfacilities$). Moreover, 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. Note that, thus far, censored and uncensored headcount ratios provide rather inconclusive evidence and that makes it difficult to render a consistent evaluation of the underlying developments. The suggested panel data-based decompositions, however, allow the causes of these observations to be examined.

[13] 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 2: Indicators, Indices and Contributions of Multidimensional Poverty

(a) Dashboard (uncensored headcount ratios)

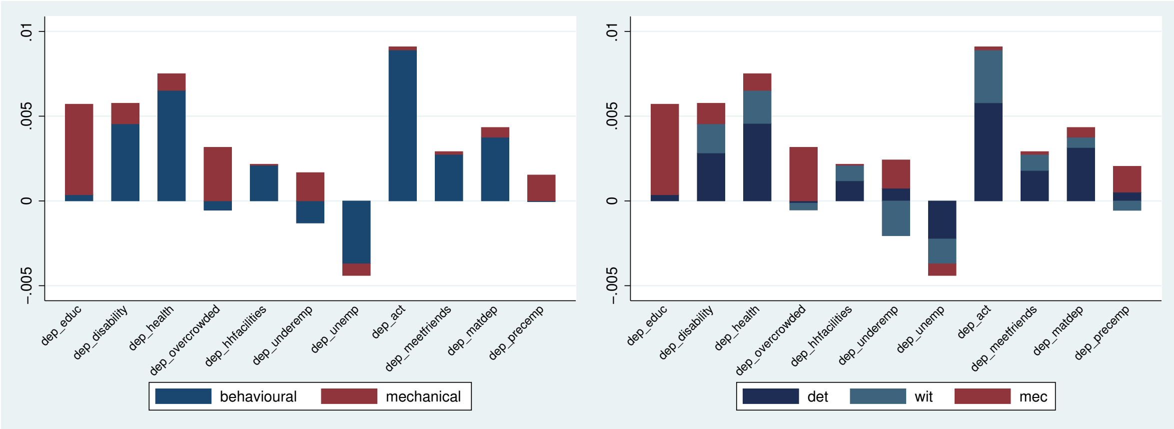
	2005	2007	Δ	δ
dep_educ	0.14924	0.14991	0.00067	0.00447
dep_disability	0.13528	0.14878	0.01350	0.09982
dep_health	0.19090	0.20971	0.01881	0.09852
dep_overcrowded	0.06056	0.05390	-0.00667	-0.11008
dep_hhfacilities	0.01563	0.01515	-0.00048	-0.03079
dep_unemp	0.06135	0.05141	-0.00995	-0.16211
dep_underemp	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	
	$k = 33$	$k = 41$	$k = 33$	$k = 41$	$k = 33$	$k = 41$	$k = 33$	$k = 41$
M0	0.03911	0.02084	0.04235	0.02354	0.00324	0.00270	0.08282	0.12950
CH	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

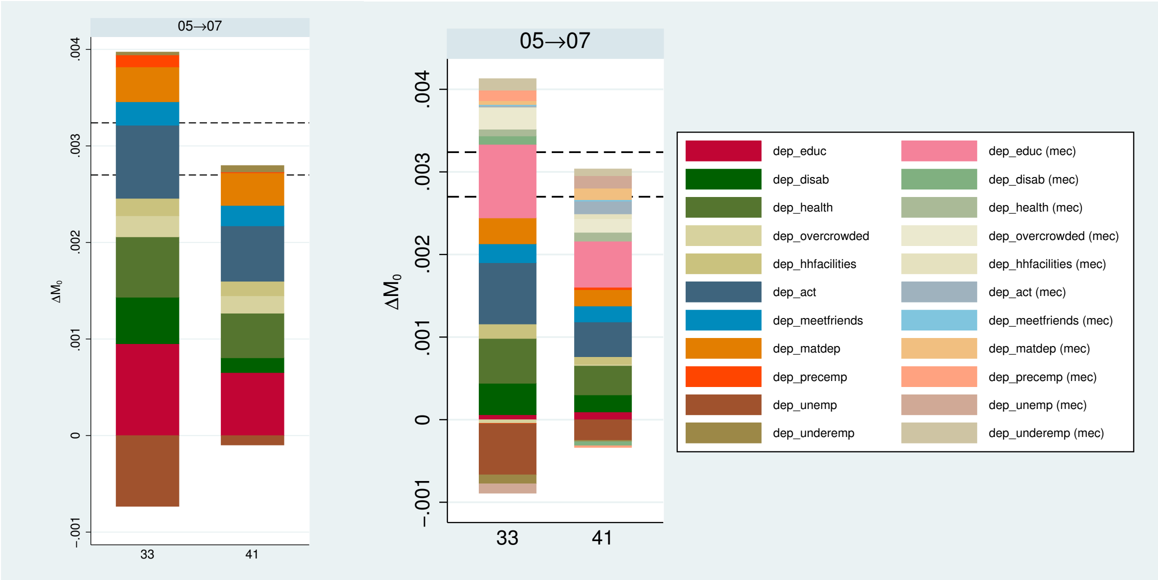


Notes: Data from SOEP. Units are absolute changes of (censored) deprivation headcount ratios (e.g. deprivation in social activities dep_act increases by approximately 0.9 percentage points).

Decomposing the Censored Headcount Ratio. In the first step equations (3) and (4) prove useful in understanding the dynamics behind these first observations better. The left graph of figure 4 reveals three particularly 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 changes (i.e. they change the censored headcount ratio in the same direction, for example, for disability or health), while in other cases mechanical changes run counter to behavioural changes (e.g. for $dep\_overcrowded$ or underemployment). Even though they are quantitatively small, these observations illustrate potential complexities that may emerge in the course of an analysis. Third, the right graph of figure 4 distinguishes behavioural transitions according to whether the poverty status changed (T_d^{det}) or whether an 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 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.

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 equation (1)). Dimensional contributions in this decomposition reflect the weighting scheme. Consequently, changes in censored headcount ratios of unemployment and education are relatively

Figure 5: Decomposing the Adjusted Headcount Ratio



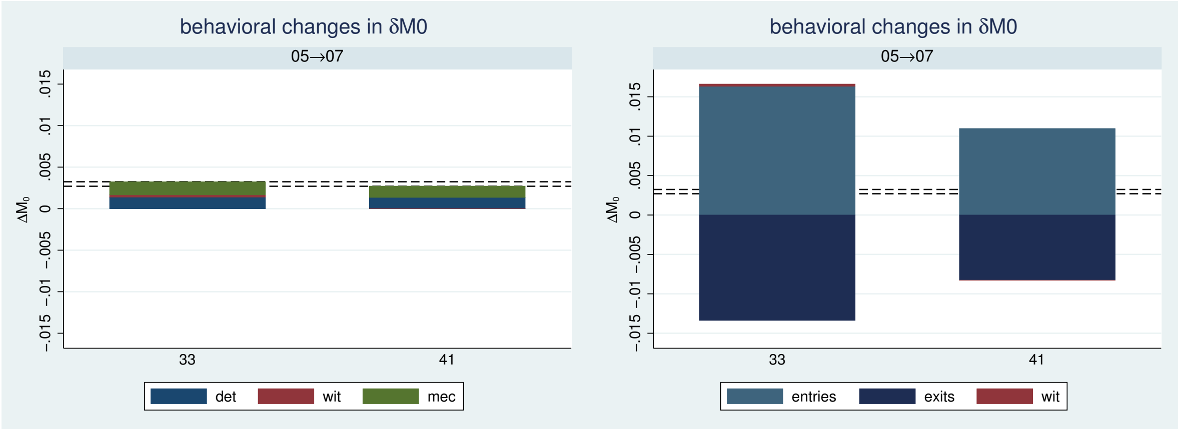
Notes: Data from SOEP. Poverty cutoffs are $k = 33, 41$. Dashed lines indicate the total change in M_0.

magnified.[14] The graph also immediately signals potential differences in the directions of changes. Taken as a whole this decomposition is a useful starting point to explore the causes of ΔM_0. Since changes in 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, for example, that the increase in dep_educ (as well as $dep\_precemp$) 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 to present many important insights.

Figure 6, on the other hand, shows two other decompositions of ΔM_0, of which the left uses equation (6) and the right equation (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 prior deprivations ($\sum T_d^{mec}$). Net changes among the poor apparently contribute little. The right graph of figure 6 reveals that high numbers of entries into and exits out of poverty affect M_0; however, they offset each other and thus indicate a rather modest net increase. An analysis would most certainly be considered incomplete if it ignored this point.

[14] Naturally, this analysis becomes more important if more indicators are weighted differently.

Figure 6: Decomposing the Adjusted Headcount Ratio II

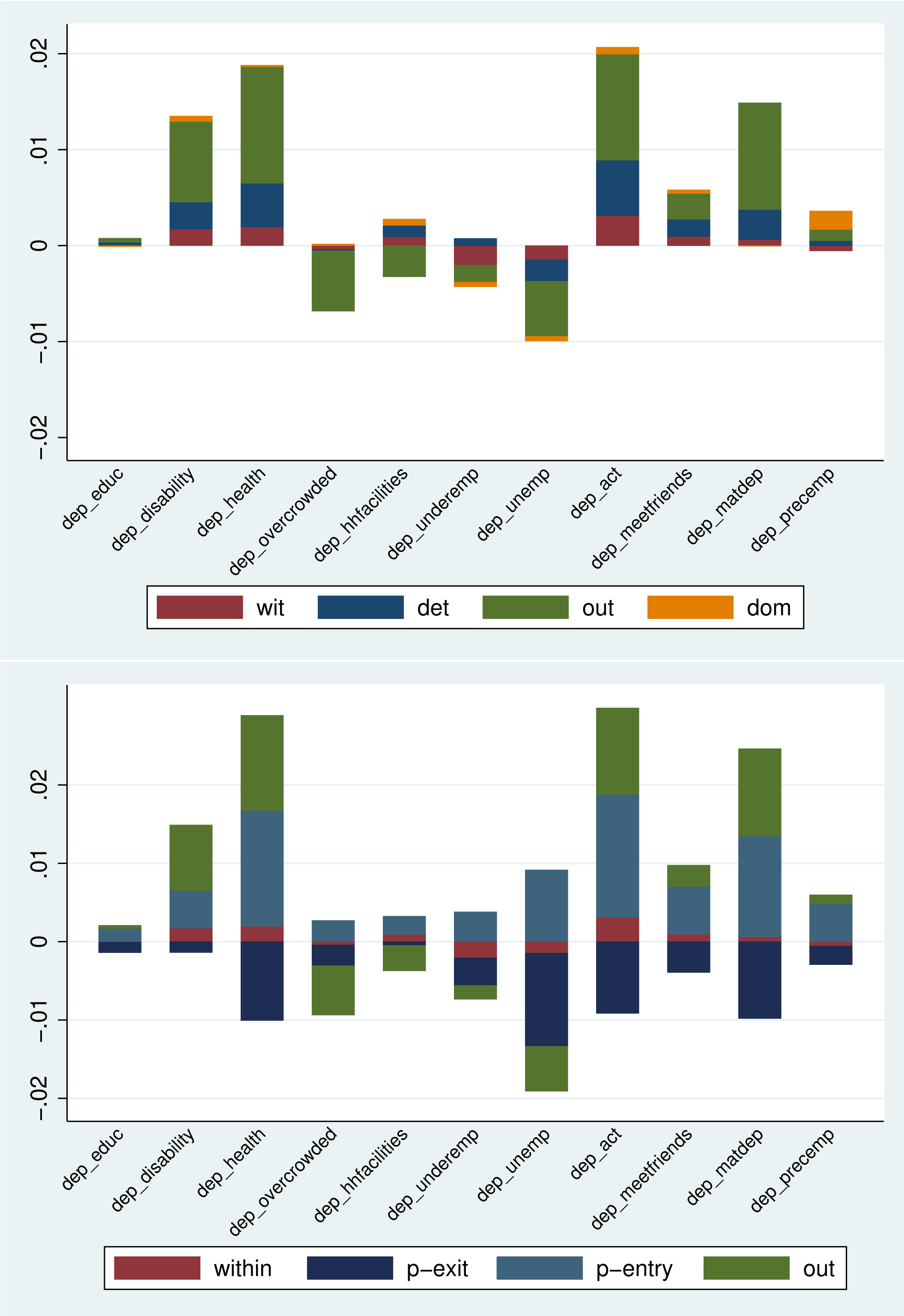


Notes: Data from SOEP. Dashed lines are ΔM_0 for $k = 33, 41$.

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 they improve or worsen the lives of the poor, or whether they mainly affect the non-poor. Figure 7 contains two possible decompositions of Δh_d. The upper one, using equation (9), shows that much of the indicator-specific transitions affect the non-poor (i.e. transitions in deprivations collected in T_d^{out}).[15] Figure 7 also shows that dominated 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. Also note that some deprivation indicators may have more complex effects, for example, $dep\_hhfacilities$ or $dep\_underemp$. The lower graph, 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.

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

Figure 7: Decomposing the Uncensored Headcount Ratio

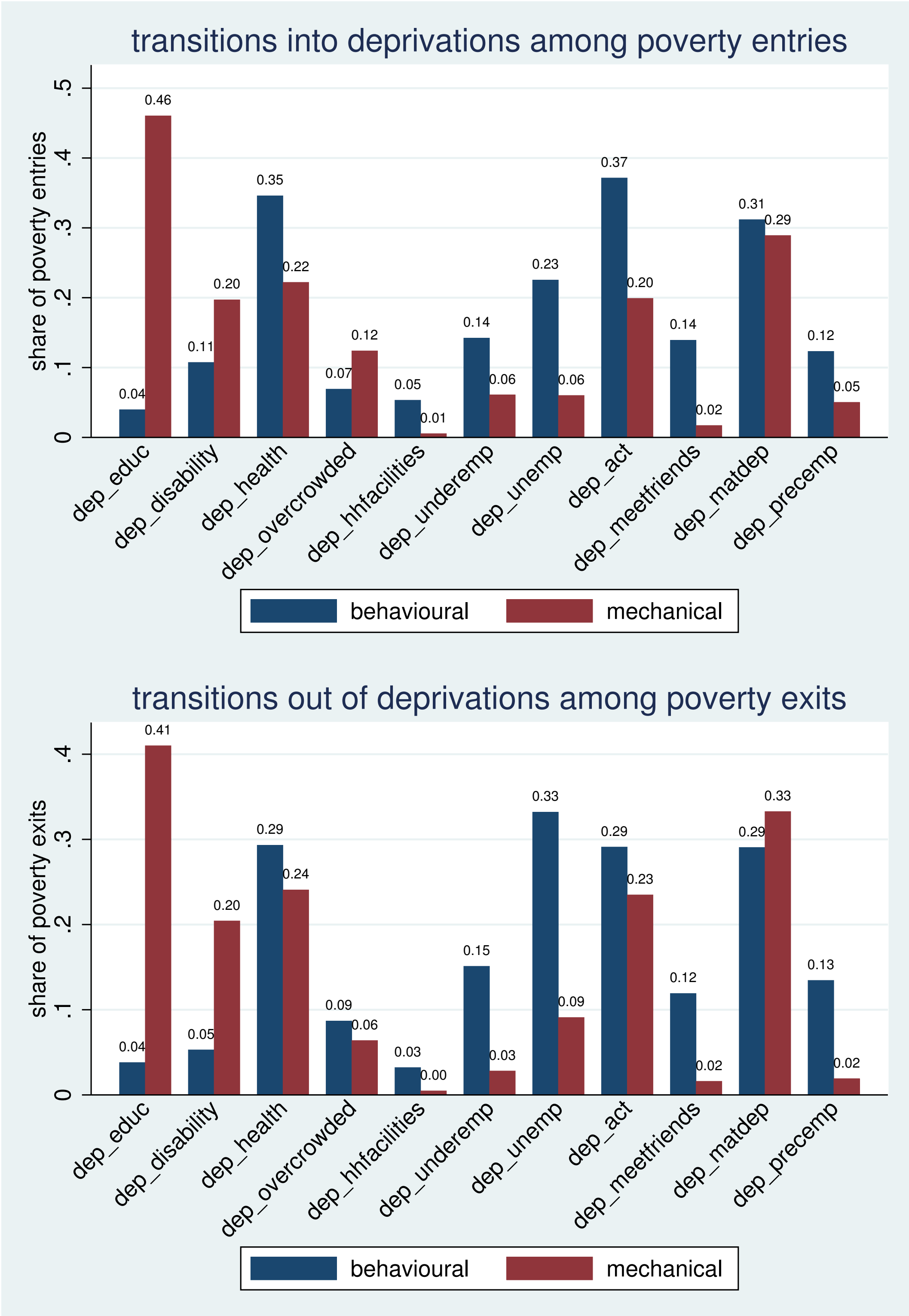


Notes: Data from SOEP. Underlying poverty cutoff is $k = 33$.

Entries and Exits of Poverty. Figure (8) provides a more in-depth analysis of poverty entries and exits. Specifically, the upper graph contains the shares of transitions into deprivations experienced by those entering poverty, whereas the lower graph shows 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% became poor when they became unemployed. Note that even percentages of behavioural 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 simply 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—sometimes 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.

Relative Performance in Deprivation Transitions. The last empirical exercise provides evidence for the question raised in section 4.1, whether the 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, the poor are, for instance, only approximately half as likely as non-poor to leave a deprivation in education. Panel (b) on the other hand, reveals the poor to be more likely than non-poor to enter another deprivation (both on the condition of being non-deprived) since most odds are larger than 1 and, in fact, several odds 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 in-

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



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

stance, 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

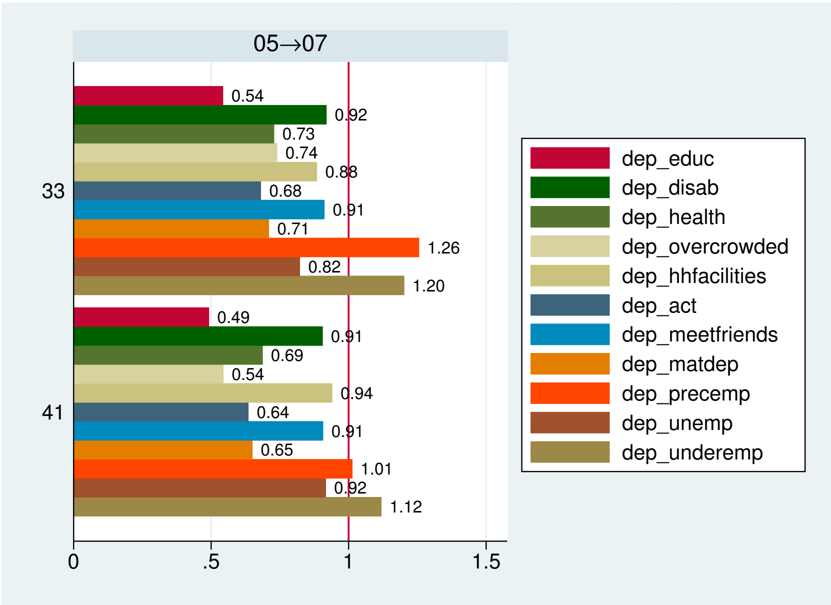
Instead of going into another summary of the data, I will conclude with some final remarks. First, this paper underlines the benefits of multidimensional poverty measures, which fulfill dimensional breakdown and subgroup decomposability. Together, both features allow a joint analysis of transitions in deprivations and poverty, and this enables the analyst to handle potentially complex interdependencies among dimensions. More importantly, as a result, the links between the raw indicators (i.e. a dashboard and the dimensional indices of multidimensional poverty) can be understood and are more easily communicable in 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 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 uncensored headcount ratio ultimately affects the poor. Additionally, if different indicators change in different directions, this may lead to complex interactions in multidimensional poverty. Even though they are traceable, these interactions may further increase the contrast to dashboard-based findings. There may, however, also be scenarios in which relying on both censored and uncensored headcount ratios simultaneously allows for reasonable conclusions. For other more complex situations, a careful year-to-year analysis using panel data is inevitable.

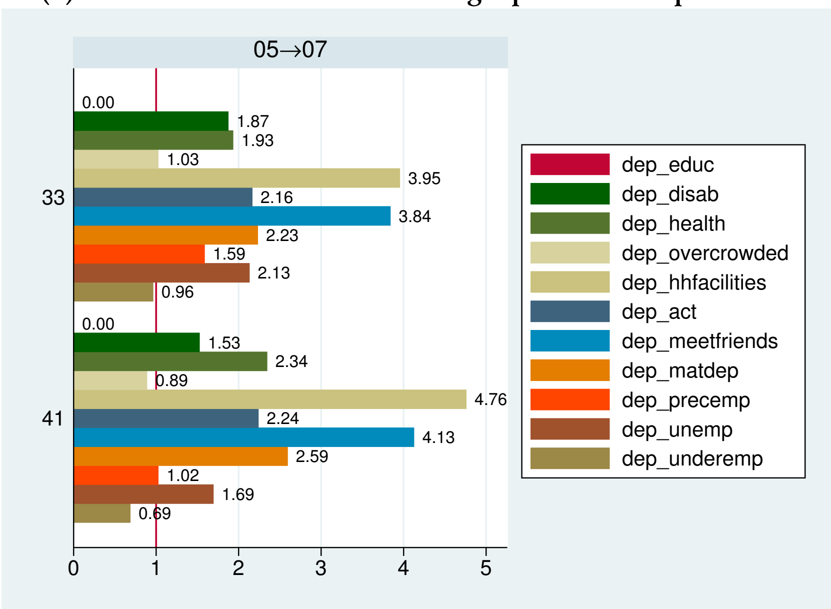
Third, in the absence of panel data there are some situations in which neither censored nor uncensored headcount ratios or their simultaneous analysis can reliably reveal behavioural on-the-ground transitions of the poor. However, this is vital for the evaluation of a policy measure and thus for policy 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 that substantially reduced deprivations in health. Then a decrease in the

Figure 9: Outflow and Inflow Ratios of Deprivations

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



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



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

censored headcount ratio of unemployment may either reflect the success of the labour market reform (through behavioural transitions) or it may signal a success of the health reform since, due to improved health, less people are considered poor despite still being unemployed (i.e. due to mechanical transitions). 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 issues like these naturally increases with the period of time 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 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, behavioural 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. 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 if one wanted to understand the increase in educational deprivation among the poor, observed in the empirical illustration, using conventional regression techniques.

Finally, as panel data sets (in particular the longer running ones) continue to be rare, a careful analysis of the existing ones—even if rather cursory—is called for. Thus, it is noteworthy that a two-year panel data analysis already allows valuable insights to be gleaned. For one, such an analysis may illuminate the process of how deprivations 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 certain deprivations tend to be. Additionally, even a two-year panel analysis can provide empirical evidence about the relative chances for the poor and non-poor to enter or leave a deprivation, thereby facilitating more reliable conclusions based on repeated cross-sectional data.

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