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Deprivations Rarely Come Alone. Multidimensional Poverty Dynamics in Europe

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ABSTRACT

This article proposes a framework to analyse micro-level dynamics inherent to multidimensional poverty measures. Specifically, I use differences in deprivation transition probabilities between multidimensionally poor and nonpoor people, to analyse how deprivations couple over time. Advantages of this approach include that it (i) summarises relevant mechanisms, (ii) requires only short-run panel data and (iii) is suitable for monitoring purposes. Using the European Union Statistics on Income and Living Conditions (EU-SILC) for 20+ countries over 2016–2020, I find that deprivations tend to couple over time. Implications include that coordinated policy programmes seem critical to overcome entrenched and prevent future deprivations.

JEL Classification: I32, O52

1 | Introduction

Measures of multidimensional poverty become more popular in both research and practice. International poverty measures are published by UNDP-OPHI (2022) and the World Bank (2022) while more than thirty countries already use a multidimensional poverty index (MPI) as an official poverty measure.[1] Even though official MPIs have been mostly applied in low- and middle-income countries, the multidimensional nature of poverty is also widely accepted in high-income countries. For instance, official poverty reports often rely on both monetary and nonmonetary indicators, whereas the European at risk of poverty or social exclusion rate already draws on several such indicators simultaneously (e.g., BMAS 2021; Social Protection Committee 2022).[2] Nonetheless, measuring poverty in affluent countries is still subject to public debate, in which MPIs feature prominently (e.g., Diekmann and Kollenbroich 2016; Conde-Ruiz and Flores Martos 2025). By now numerous proposals for high-income countries have been made (e.g., Whelan et al. 2014; Weziak-Bialowolska 2016; Dhongde and Haveman 2017; Suppa 2018a; Alkire and Apablaza 2017; Mitra and Brucker 2019).

Previous work on multidimensional poverty usually draws on individual or repeated cross-sectional data and so dynamics are usually studied as changes over time in aggregate measures (e.g., Alkire, Apablaza, et al. 2017; Burchi et al. 2022; Alkire et al. 2023). By contrast, panel data are rarely used and if so they are analysed in different ways. Some studies exploit the longitudinal structure to measure chronic multidimensional poverty (e.g., Alkire, Roche, and Vaz 2017; Alkire, Apablaza, and Guio 2021), while others evaluate programs (e.g., Borga and D'Ambrosio 2021). A major constraint for such dynamic analyses is the lack of high-quality panel data for most countries and if available, surveys usually run only for a short period.[3] As a consequence, very little is known about multidimensional poverty dynamics at the micro-level. Yet, many theoretically important questions would ideally be addressed with long-run panel data, such as whether and how experienced deprivations in some dimensions beget further deprivations in other dimensions. Building on Apablaza and Yalonetzky (2013) and Suppa (2018a), who examine transitions in multidimensional poverty within the popular Alkire and Foster (2011) approach, the present article proposes a framework to harness short-run panel data for the analysis of multidimensional poverty dynamics at the micro-level.

Multidimensional poverty measures rest upon a set of deprivation indicators, where each of them reflects a critical shortfall in a particular dimension of human well-being. Depending on the country context, deprivation indicators may reflect, for instance, critical nutritional outcomes, lack of access to safe drinking water or sanitation facilities, poor housing conditions, children not attending school, unemployed adults, specific health issues, particular forms of material or social deprivation, among others. Poverty, instead, is usually defined as multiple deprivation. An important feature of the proposed framework is that it permits to analyse the dynamics among these deprivation indicators of the multidimensional poverty measure itself; in other words measure-inherent dynamics. While related research frequently analyses the links between individual outcomes related to potential deprivations indicators, such as the role of poor housing conditions or material deprivation for poor health (e.g., Angel and Bittschi 2017; Blázquez et al. 2013; Adena and Myck 2014), related dynamics have so far neither been studied in a coherent framework of multidimensional poverty, nor jointly for several deprivation indicators.

To illustrate the proposed framework, this article develops a summary measure, which permits assessing whether all in all, the deprivations of multidimensional poverty (e.g., low education, poor health or low living standard) tend to couple or decouple over the previous year. More specifically, this article suggests examining differences in deprivation entry and exit probabilities between poor and nonpoor (henceforth *poor* always refers to *multidimensionally* poor). These differences in transition probabilities allow us to assess whether poor people are (i) more likely to enter a new deprivation and (ii) less likely to leave an existing deprivation than comparable nonpoor. The measures of interest can be easily obtained from a single dynamic linear model per deprivation indicator and may be annually computed. Related estimates, therefore, permit monitoring and assessing whether dynamics in a particular deprivation indicator have been rather pro- or anti-poor over the previous year. Relying on the past poverty status to distinguish transition rates thus offers a useful summary of individual effects and, moreover, mitigates problems relevant in practice such as small cell sizes and over-testing. All three advantages of 'summary index tests' have been previously recognised (e.g., Anderson 2008, 1484). The developed framework may also be adapted for other similar purposes, such as an in-depth analysis of country differences in the process of coupling of deprivations or the evaluation of a shock on these processes.

In the empirical analysis, I apply this approach for more than 20 countries using panel data of the European Union Statistics on Income and Living Conditions (EU-SILC) over 2016–2020 with an MPI which is broadly consistent with previous work using the same data (e.g., Weziak-Bialowolska 2016; Alkire and Apablaza 2017; Alkire, Apablaza, and Guio 2021). In general, the results suggest that deprivations tend to couple, with patterns rather stable over time for most indicators. More specifically, I find that multidimensionally poor people are both less likely to leave an experienced deprivation and more likely to enter an additional deprivation. In other words, deprivations tend to be more persistent for poor people and, at the same time, poor people are more prone to further deprivations. I do not find evidence that the main findings systematically differ when poor people are required to suffer from a particular deprivation (such as low education). The presented evidence re-enforces the critical role of coordinated policy programmes across departments to effectively overcome multiple deprivation, which has been previously suggested (e.g., Stiglitz et al. 2009, 55–56). Nonetheless, I also observe both year-to-year and cross-country variations.

The proposed approach is particularly useful for research on multidimensional poverty as it permits to coherently analyse the interplay of its deprivation indicators which so far has not received much attention. Previous research usually studies statistical associations of variables external to the measure itself, whether in form of disaggregations (e.g., Alkire Oldiges, and Kanagaratnam 2021), macro-level regressions (Santos et al. 2019; Jindra and Vaz 2019) or micro-level treatment evaluations (Seth and Tutor 2021; Borga and D'Ambrosio 2021). Some studies also rely on mathematical decomposition techniques (Alkire and Foster 2011; Roche 2013). Measure-inherent dynamics have so far been neglected largely because they escape cross-sectional analyses, as the contemporaneous correlation among deprivation indicators is already used for the measurement itself (to identify the multiply deprived as poor). Deprivation indicators are, however, relevant beyond their intrinsic role in the measurement exercise (where they capture critical shortfalls from a normative perspective). Specifically, deprivations indicators are also instrumentally relevant for achievements in other dimensions of human well-being (e.g., good health is conducive to achieving good education); see Sen (1999 ch. 2), for this distinction. Consequently, methods to study associations among deprivation indicators, which go beyond the poverty measurement itself, while being consistent with it, are much needed. In this article, I suggest to ground analyses of the interplay of the deprivation indicators on their intertemporal correlation, while leaving their contemporaneous correlation for the measurement exercise—and that in a way which (i) respects the nature of multidimensional poverty measurement, (ii) provides instructive and novel insights into the coupling processes of deprivations and (iii) is feasible with the available data.

Finally, the presented approach may also be applied beyond multidimensional poverty in other fields which also rely on the Alkire and Foster (2011) approach, such as quality of employment measures (Sehnbruch et al. 2020; Apablaza et al. 2022), women empowerment indices (Alkire et al. 2013; Malapit et al. 2019), energy poverty (Nussbaumer et al. 2012) or deprivations in other dimensions (Suppa 2021).

The article is organised as follows. Section 2 introduces the data and explains how multidimensional poverty may be measured in Europe. Section 3 details the proposed framework and provides both theoretical considerations and the empirical approach. Section 4 shows the results and Section 5 provides their discussion. Finally, Section 6 offers some concluding remarks.

2 | Measuring Multidimensional Poverty in Europe

The analysed poverty measure is constructed using the Alkire and Foster (2011) approach, which also underlies the global MPI (Alkire and Santos 2014; UNDP-OPHI 2022) and more than thirty national MPIs. Consider $i = 1, \dots, N$ individuals and $t = 1, \dots, T$ periods of time. Further let $y_{ijt} \in \mathbb{R}^+$ denote the $j = 1, \dots, D$ observable achievements relevant for poverty measurement and z_j the critical deprivation thresholds. An individual is deprived in achievement j at time t if $d_{ijt} = \mathbb{I}(y_{ijt} < z_j)$, where $\mathbb{I}(\cdot)$ is the indicator function. Let the deprivation score be $c_{it} = \sum_j w_j d_{ijt}$ where $w_j \in (0, 1)$ with $\sum_j w_j = 1$ are the normative weights. Then an individual is considered poor if $\text{poor}_{it} = \mathbb{I}(c_{it} \geq k)$, where k with $k \in (0, 1]$ is the cross-dimensional poverty cutoff. Finally, let $Q_t = \{i | \text{poor}_{it} = 1\}$ denote the set of all poor people in t and q_t the number of all poor people in t. Then the headcount ratio, which shows the proportion of poor people in the population, is $H_t = \frac{q_t}{N}$. The intensity, which shows the average deprivation among the poor, is $A_t = \frac{1}{q_t} \sum_{i \in Q_t} c_{it}$. The product of both partial indices is the adjusted headcount ratio $M_t = H_t \times A_t$ (although neither M_t, nor A_t are explicitly used in this study). Additionally, one may obtain deprivation-specific uncensored and censored headcount ratios as $h_{jt} = \frac{1}{N} \sum_i d_{ijt}$ and $\underline{h}_{jt} = \frac{1}{N} \sum_{i \in Q_t} d_{ijt}$, respectively. The former reports the proportion of the population which is deprived in a particular indicator, whereas the latter shows the proportion of the population which is both poor and deprived in that particular indicator. See Alkire et al. (2015) for a more comprehensive presentation.

2.1 | Measure

The multidimensional poverty measure I analyse is broadly in line with previous research using the same data and can be conceptually integrated into the capability approach (e.g., Sen 1992, 1999). More specifically, the measure comprises eight deprivation indicators, organized in five dimensions; see Table 1 for details. Indicator selection and construction largely follow previous research (Weziak-Bialowolska 2016; Alkire and Apablaza 2017; Alkire, Apablaza, and Guio 2021) and most deprivation indicators are primary or secondary indicators of the European social inclusion framework (Social Protection Committee 2022, section 5.1), with which the present measure is aligned. Differences with previously proposed measures emerge from data constraints. For instance, responses to some survey questions (e.g., unmet medical needs, exposure to noise or crime), which are used in Weziak-Bialowolska (2016); Alkire and Apablaza (2017), are only distributed with the cross-sectional component of the EU-SILC and thus unavailable for the present analysis. Other information (e.g., on social activity or detailed wealth information), which would permit, for instance, refined deprivation indicators for social participation, as suggested in (Suppa 2021), are only collected in individual survey years and thus also unavailable

TABLE 1 | Specification of the multidimensional poverty measure.

Dimension	Deprivation indicator	Weight
Health	Self-reported health (bad or very bad)	1/10
	Limitation in activities due for health problems	1/10
Education	Primary education or less	1/5
Housing	Housing conditions (e.g., leaking roof)	1/10
	Overcrowding index	1/10
Employment	Low work intensity	1/5
Living Standard	Material and social deprivation index	1/10
	Low income (less than 60% of median HH net equiv.)	1/10

Note: The cross-dimensional poverty cutoff is $k = 2/5$.

for subsequent analyses. The adopted equal-nested weighting scheme, which assigns equal weights to all dimensions and equal weights to all indicators within dimensions, can motivated by the view that none of the considered dimensions is substantially more important than the others. Moreover, the equal-nested weighteing scheme has been widely applied before (e.g., Alkire and Apablaza 2017).

The adopted measure identifies poverty at the individual level and subsequent analyses are also restricted to the adult population, see also, for example, Weziak-Bialowolska (2016); Suppa (2018a) for previous measures at the individual-level.[4] As individual-level deprivations are directly observed for every respondent and, moreover, household-level deprivations (e.g., in housing conditions) can be reasonably assumed to afflict all household members, one advantage of this approach is that all individuals can truly experience all deprivations, in principle.[5] The main advantage for the present context is, however, that an individual-level measure offers an unobstructed view on the transitions in deprivations, which are at the center stage of this study. In contrast, dynamic analyses at the household level would additionally have to account for household formation, split-off, and dissolution over time, which may change the deprivation status of a household as well.

The preferred cross-dimensional poverty cutoff is $k = 0.4$ as this choice implies that an individual has to suffer from (complete) deprivations in at least two dimensions (so true multiple deprivation). Additionally, this choice permits meaningful sensitivity checks within a plausible range of parameters as well as informative analyses in the present cross-country setting. The main findings also hold for alternative cutoffs ($k = 0.3$ and $k = 0.5$). Values outside this range increasingly imply nonoverlapping deprivations, vanishing poverty and, more generally, smaller cells sizes (e.g., of poor and deprived people).

2.2 | Data

The subsequent analyses use the official microdata of the European Union Statistics on Income and Living Conditions

(EU-SILC) for 22 countries, which are widely used for monitoring purposes of various social inclusion indicators in the European Union (Eurostat 2021; Wirth and Pforr 2022).[6] The target population are private households and their current members. The analysis draws on the longitudinal component of the data with a period of observation of 2016–2020. Using earlier data rounds would imply additional compromises for the deprivation indicator construction.[7] The EU-SILC follows a rotating panel structure. Each year a new sub-sample (also called rotational group) starts and its respondents are followed for some time until they are eventually replaced by a new sub-sample. Countries may have four or more rotational groups. Each subgroup is supposed to be representative of the entire population in a particular year and would allow, for example, a cross-sectional estimate for that year. Figure 1 illustrates the rotating panel structure of the EU-SILC for a country with four rotational groups.

The EU-SILC is distributed in two variants. The cross-sectional component of the data for a particular year comprises all four subsamples observed in that year from different rotational groups (see the blue box in Figure 1 for the 2019 cross-section). The estimation of a cross-sectional quantity (e.g., the poverty rate in a particular year) would use all four available subsamples for efficiency reasons. The longitudinal component of the data for a particular year comprises all observations of those three rotational groups which have been previously observed, too (see the red box in Figure 1 for the 2019 longitudinal sample). An estimate which explicitly draws on the panel component, such as the proportion of people poor in both current and previous periods, may only use three subsamples (as the fourth group just started and does not provide any information for previous years). Similarly, estimating the proportion of people poor in the current period who were also poor in all three previous periods would have to be based on a single rotational group (in Figure 1 rotational group 3 would allow such an estimate for 2019.)

The objective of the present article is to analyse year-to-year changes and test specific hypotheses in this context. For more precise estimates, for example, in the analysis of the change to 2019, I, therefore, use a balanced 2-year panel comprising all rotational groups observed in those two years (grey boxes in Figure 1).

All analyses use the longitudinal weights for a balanced 2-year panel as provided by Eurostat, which account for complex survey design, nonresponse adjustments (including panel attrition) usually by rotational group, age groups sex and region for most countries.[8] Using EU-SILC data from 2016–2020, I can analyse four changes (from 2016–2017 to 2019–2020).

The subsequent empirical analysis focuses on Spain to streamline the presentation while results for other countries are largely deferred to Appendix A. Before turning to actual analysis, Figure 2 shows basic estimates for Spain and selected countries to provide context. In terms of the headcount ratio (left figure), Spain experiences an incidence of about 15% throughout the period of observation. Instead, other countries with initially higher or similar headcount ratios reduce their incidence by about 5%-points. Portugal or Greece, for instance, have higher incidences whereas, for example, Hungary and Poland have initially similar incidences. Turning to the indicator-specific uncensored headcount ratios, the right-hand graph in Figure 2 suggests slight reductions for some indicators (e.g., low education and work intensity) and slight increases for others (e.g., overcrowding). A salient observation is certainly the increase in poor housing conditions and limitations through health in 2020, which is most likely related to the then unfolding covid pandemic. However, results for 2020 should be interpreted with caution, as the pandemic and related policy responses also induced considerable changes in the interview mode.

3 | Framework

3.1 | Theoretical Considerations

Multidimensional poverty measures capture overlapping deprivations and, moreover, permit to measure poverty conceptualised as *multiple* deprivation. Various mechanisms may result in the coupling of deprivations. For instance, low education may first result in more and longer spells of unemployment and material deprivation, which then together also deteriorate health over time. Such indicator dynamics have been previously studied, however, neither coherently in a multidimensional poverty framework, nor jointly for several indicators.

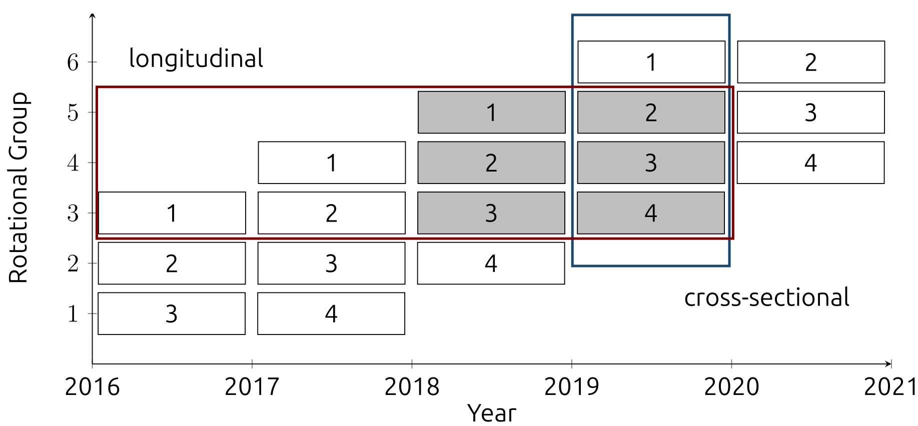

FIGURE 1 | Rotating panel structure. Boxes refer to observations of rotational groups; grey boxes show subsamples used for the analysis of the change to 2019. Further groups ending in 2016 or starting in 2020 are omitted.

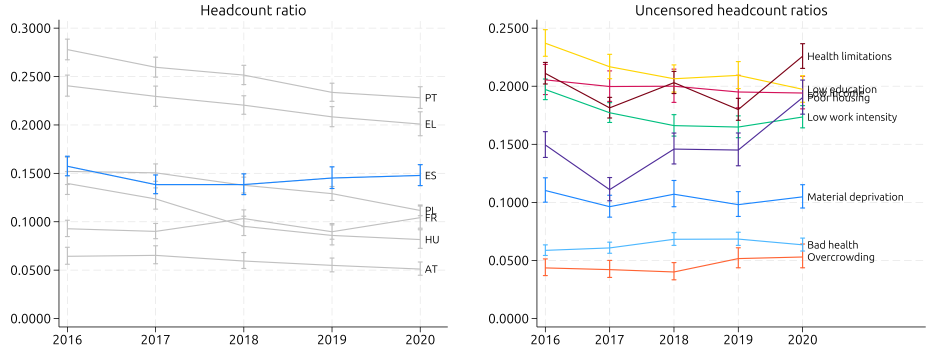

FIGURE 2 | Headcount ratio and uncensored headcount ratios for Spain. 95%-confidence intervals account for survey design using information on primary sampling units and regions for stratification.

More specifically, previous research lends support for associations of every possible combination of two deprivation indicators, even though the identification of the causal direction or specific mechanisms has been ignored for a long time; for health outcomes, for instance, see Smith (1999) and Fuchs (2004). More recent studies, however, seek to provide estimates permitting a causal interpretation. For instance, for health outcomes Angel and Bittschi (2017) explore the effect of housing conditions, Blázquez et al. (2013) the effect of material deprivation and Drydakis (2015) the role of unemployment. Increasingly available panel data also permit the study of deprivation entries and exits separately (e.g., Adena and Myck 2014), which is a concern that also figures prominently in monetary poverty dynamics since Bane and Ellwood (1986).

Taken together deprivations in general may steadily accumulate over time if (i) each deprivation features a certain persistence, (ii) already experienced deprivations involve further deprivations, (iii) existing deprivations make leaving other deprivations more difficult or a combination thereof. In practice individuals may be subject to several mechanisms at the same time and, moreover, some of those mechanisms may only slowly unfold their effect over time (e.g., health deterioration). Additionally, some deprivations, such as low education may function as moderators of one or more other mechanisms. Specifically, education has been considered in both economics and sociology for a long time to improve individuals' decision-making when facing changing circumstances, including economic shocks (Fullan and Loubser 1972; Schultz 1975). In line with this, Riddell and Song (2011) find higher education to increase the re-employment probability conditional on being unemployed beforehand. Modelling and analysing all these relations explicitly would put extremely high demands on the data (including the structure of a long-running panel). Instead, one way to summarise the previous considerations is to expect poor people (who experience multiple deprivations by definition) to be more likely to enter a particular deprivation, which they do not experience than comparable nonpoor (who neither suffer from that deprivation). Likewise, one may expect poor people to be less likely to leave a particular deprivation than comparable nonpoor who do, however, experience that particular deprivation. See Suppa (2018b) for similar, but more ad-hoc hypotheses.

One advantage of formulating hypotheses concerning the poverty status, which essentially pools various deprivation-specific mechanisms, is that it allows for general assessments summarising recent deprivation entry and exit patterns. Other advantages include that a focus on the poverty status may help to mitigate issues of small cell sizes (which are often related to marginally significant results) and over-testing. Indeed, all three advantages of 'summary indices' at the micro level have been recognised in previous research (Anderson 2008). Naturally, where needed this summary may be unpacked to explore specific mechanisms for entries or exits of a particular deprivation.

3.1.1 | Conditional Probabilities of Interest

To formulate these hypotheses more formally, it is helpful to introduce the following four transition probabilities.

$$\Pr(d_{ijt} = 1 \mid \text{poor}_{it-1} = 0 \ \wedge \ d_{ijt-1} = 0) \tag{CP.1}$$

$$\Pr(d_{ijt} = 1 \mid \text{poor}_{it-1} = 1 \ \wedge \ d_{ijt-1} = 0) \tag{CP.2}$$

$$\Pr(d_{ijt} = 0 \mid \text{poor}_{it-1} = 0 \ \wedge \ d_{ijt-1} = 1) \tag{CP.3}$$

$$\Pr(d_{ijt} = 0 \mid \text{poor}_{it-1} = 1 \ \wedge \ d_{ijt-1} = 1) \tag{CP.4}$$

Equations (CP.1) and (CP.2) are the probabilities to enter deprivation j for nonpoor and poor individuals, respectively. Instead, equations (CP.3) and (CP.4), are the probabilities to exit deprivation j for nonpoor and poor individuals, respectively.

3.1.2 | Hypotheses

The main hypotheses may then be formulated as follows. First, since poor individuals are by definition already deprived in several other deprivations in $t-1$, one may also expect them to be more likely to enter a new deprivation j in t, which they do not experience in $t-1$, compared with nonpoor and who were also not j-deprived in $t-1$. So the first hypothesis, expressed as a difference in deprivation entry probabilities is

$$\Delta_j^{\text{entry}} = \Pr(d_{ijt} = 1 \mid \text{poor}_{it-1} = 1 \ \wedge \ d_{ijt-1} = 0) - \Pr(d_{ijt} = 1 \mid \text{poor}_{it-1} = 0 \ \wedge \ d_{ijt-1} = 0) > 0 \tag{H.1}$$

Second, since the poor by definition already experience several other deprivations, they may be less likely to leave deprivation j they already experience in $t-1$, than the nonpoor who are deprived in j in $t-1$. So the second hypothesis, expressed as a difference in deprivation exit probabilities is

$$\Delta_j^{\text{exit}} = \Pr(d_{ijt} = 0 \mid \text{poor}_{it-1} = 1 \wedge d_{ijt-1} = 1) - \Pr(d_{ijt} = 0 \mid \text{poor}_{it-1} = 0 \wedge d_{ijt-1} = 1) < 0 \quad \text{(H.2)}$$

Third, a priori there is no reason to expect the poverty status to play quantitatively the same role for both deprivation entries and exits. Specifically, poverty may increase the deprivation entrance probability *more* or *less* than it reduces the deprivation exit probability. Evidence in support of either direction would suggest distinguishing deprivation entries and exits in any analysis. Thus, the third hypothesis is that the absolute value of the increase in the deprivation entrance probability is not equal to the absolute value of the decrease in the deprivation exit probability, or formally

$$\mid \Delta_j^{\text{entry}} \mid \neq \mid \Delta_j^{\text{exit}} \mid \quad \text{(H.3)}$$

Fourth, if deprivations are persistent, then the current deprivation status depends on the past deprivation status. Given the formalisation above, a fourth hypothesis to explore in this context is whether current deprivation status depends on past deprivation status ($\Pr(d_{ijt} \mid d_{ijt-1})$), which would reflect the persistence of deprivations. If deprivations are persistent then people deprived in $t-1$ are more likely to be deprived in t than nondeprived or formal

$$\Pr(d_{ijt} = 1 \mid d_{ijt-1} = 1) > \Pr(d_{ijt} = 1 \mid d_{ijt-1} = 0) \quad \text{(H.4)}$$

The subsequent empirical analyses will seek to reject the respective null hypotheses of equality in all four cases.

3.2 | Empirical Approach

3.2.1 | Binary Model

One way to obtain all the conditional probabilities introduced in the previous section is to fit a binary choice model for different subsamples (i.e., individuals who enter and leave a deprivation, respectively) and subsequently estimate the average predicted probabilities evaluated at the respective d_{ijt-1} and poor_{it-1}. Formally these models can be written as

$$\Pr(d_{ijt} = 1) = F(\alpha_1 + \beta_1 \, \text{poor}_{it-1} + \epsilon_{1ijt}) \quad \forall d_{ijt-1} = 0 \quad \forall j \quad (1)$$

$$\Pr(d_{ijt} = 0) = F(\alpha_0 + \beta_0 \, \text{poor}_{it-1} + \epsilon_{0ijt}) \quad \forall d_{ijt-1} = 1 \quad \forall j \quad (2)$$

where $F(\cdot)$ is a cumulative distribution function. Equation (1) is a model for deprivation entries (the analysed event is deprivation) and may be estimated using a sample of observations that are not deprived in indicator j in $t-1$. Instead, Equation (2) is a model for deprivation exits (the analysed event is nondeprivation) and may be estimated using a sample of observations who are deprived in indicator j in $t-1$. Using these models the average predicted entry probabilities for poor and nonpoor may be obtained as $F(\alpha_1 + \beta_1)$ and $F(\alpha_1)$. Their difference corresponds to partial effect of poor_{it} on the deprivation probability:

$$\frac{\Delta \Pr(d_{ijt} = 1)}{\Delta \text{poor}_{it-1}} = F(\alpha_1 + \beta_1) - F(\alpha_1) \quad (3)$$

Instead of estimating models (1) and (2) separately, joint estimation is preferable. Besides efficiency gains, all three hypotheses may be explored based on a single estimation. First, observe that Equation (1) models the deprivation event, whereas Equation (2) models the nondeprivation event. In binary choice models, however, the parametrization of the event probability also implies the parametrization of the complementary probability. Accordingly β_0 (from model (2)) may also be used to compute the complementary (staying deprived) probability $\Pr(d_{ijt} = 1)$. Effectively, only the signs of the coefficients would change. Introducing, moreover, the past deprivation status and its interaction with the past poverty status gives a combined flexible model, which allows to analyse deprivation exits and entries, as follows

$$\Pr(d_i = 1) = F(\alpha + \beta \text{poor}_{it-1} + \gamma d_{it-1} + \delta \text{poor}_{ijt-1} \times d_{ijt-1} + \epsilon_{it}) \quad \forall j \quad (4)$$

3.2.2 | Linear Probability Model

The main interest of this article is to explore hypotheses related to differences in conditional probabilities, which are essentially differences in particular average predicted probabilities. As the linear probability model (LPM) often approximates the partial effects of explanatory variables well (Wooldridge 2010, 562–565) and, moreover, related hypothesis testing is also straightforward (if heteroskedasticity-robust standard errors are used), I focus on estimates of the LPM below. While Table A2 in Appendix A shows for selected country-year combinations that both the LPM and a logit model produce nearly identical average predicted probabilities, future applications of these analyses may have to revisit this decision, in particular if individual predicted probabilities are used.[9] The linear model may be written as follows:

$$\Pr(d_{ijt} = 1) = \alpha + \beta \text{poor}_{it-1} + \gamma d_{ijt-1} + \delta \text{poor}_{ijt-1} \times d_{ijt-1} + \epsilon_{it} \quad \forall j \quad (5)$$

Besides a slightly faster estimation, one advantage of the linear model is that average predicted probabilities can be directly obtained from the coefficients of the model, that is,

$$\Pr(d_{ijt} = 1 \mid \text{poor}_{it-1} = 0 \wedge d_{ijt-1} = 0) = \alpha \quad (6)$$

$$\Pr(d_{ijt} = 1 \mid \text{poor}_{it-1} = 1 \wedge d_{ijt-1} = 0) = \alpha + \beta \quad (7)$$

$$\Pr(d_{ijt} = 0 \mid \text{poor}_{it-1} = 0 \wedge d_{ijt-1} = 1) = 1 - (\alpha + \gamma) \quad (8)$$

$$\Pr(d_{ijt} = 0 \mid \text{poor}_{it-1} = 1 \wedge d_{ijt-1} = 1) = 1 - (\alpha + \beta + \gamma + \delta) \quad (9)$$

Note that the deprivation exit probabilities are obtained as complementary probabilities from the model estimates.

3.2.3 | Coefficient Interpretation

How are the different coefficients now to be interpreted? First, γ reflects the role of past deprivation for current deprivation. For a persistent deprivation $\gamma > 0$. Instead, β reflects the role of past poverty in current deprivation. Assuming the coefficient of the interaction term $\delta = 0$ for the moment, $\beta > 0$ means that the poor are more likely to enter the deprivation *and* less likely to leave the deprivation. The coefficient of the interaction term δ permits, however, the role of past poverty on current deprivation status (as captured by β) to differ for deprivation entries and exits. Specifically, a positive (negative) δ would mean that past poverty status is quantitatively more (less) important for deprivation exits than for deprivation entries. Importantly $\delta \neq 0$ also suggests analysing deprivation entries and exits separately. An interesting special case is $\beta + \delta = 0$, which means that the poverty status increases the deprivation entry probability, but does not affect the deprivation exit probability. Conversely, $\beta = 0$ and $\delta > 0$ suggest that past poverty is irrelevant for deprivation entries but decreases the probability of deprivation exits.

Finally, the measures of interest, the differences of entry and exit probabilities between poor and nonpoor can be easily computed using the coefficients of the linear model as $\Delta_j^{\text{entry}} = \beta$ and $\Delta_j^{\text{exit}} = -(\beta + \delta)$. Similarly, using the coefficients of the linear model, the four hypotheses can be simply written as (i) $\beta > 0$, (ii) $-(\beta + \delta) < 0$, (iii) $\delta \neq 0$, and (iv) $\gamma > 0$.

4 | Results

4.1 | Transition Rates

Before turning to the regression results, Figure 3 shows the overall deprivation exit and entry rates for Spain over time. In general deprivation entry rates tend to be relatively smaller than exit rates. This observation partly follows from different reference populations, which are relatively large for entry probabilities (all people who are not deprived in a particular indicator) and relatively small for exit probabilities (people who are already deprived in that indicator). Since deprivation indicators frequently identify smaller proportions of the population, this pattern can be expected to be observed more generally. Moreover, the level of transition rates varies by indicator, too. For instance, exit rates for low income or low work intensity are about 0.3 whereas those for material deprivation and housing quality are about 0.5 and 0.6 in 2019 (both declining from even higher levels), respectively. Deprivation entry rates tend to be 0.1 or less. Subsequent analyses explore these transition rates further and in particular their relation with the multidimensional poverty status in the previous period.

4.2 | Coefficients

Table 2 presents estimates for the coefficients of the linear model for Spain in 2019, see Table A1 for three further examples (Austria, Belgium and Poland). Several important observations emerge. First, past deprivation status is usually highly relevant for current deprivation status; the estimate of the related coefficient $\hat{\gamma}$ is positive and significant at the 1%-level in most instances. Moreover, the estimate for the coefficient of the past poverty status $\hat{\beta}$ is positive and significant in most instances, as well. Seen individually, it only refers to deprivation entries; for deprivation exits the estimated coefficient of the interaction term ($\hat{\delta}$) is to be taken into account as well. The results for this interaction term are of particular interest at this stage as they allow us to assess whether the subsequent analysis should report results separately for deprivation entries and exits. Table 2 shows that estimated coefficients of interaction terms are often positive and sometimes insignificant or even negative.[10] Note that if either deprivation entries or exits are not observed, neither γ nor δ can be estimated for lack of information (e.g., as in the case of low education). This issue of small cell sizes surfaces also in other countries and becomes by tendency more relevant for better-off countries and smaller samples or both.

Broadly speaking the results suggest, that (i) the poverty status is usually relevant for both deprivation entries and exits, (ii) the past poverty usually affects deprivation entries and exits to a different extent, although results vary by country and indicator (iii) the evidence supports persistence of deprivations, (iv) specific results may vary with country and year and (v) small cell sizes may even matter to the extent that occasionally coefficients cannot be estimated at all.

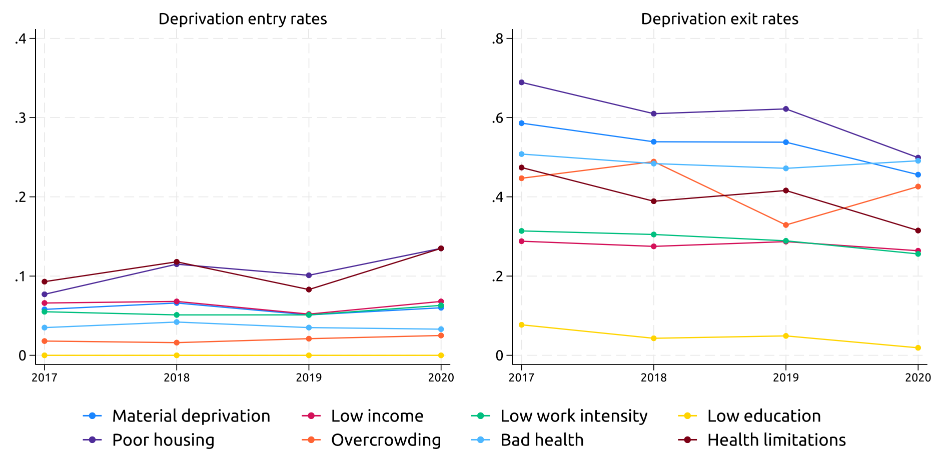

FIGURE 3 | Transition rates over time in Spain by deprivation indicator.

TABLE 2 | Estimated coefficients or further countries–linear model.

Spain 2019								
	(1) MD	**(2) LI**	**(3) LWI**	**(4) LE**	**(5) PH**	**(6) OC**	**(7) BH**	**(8) HL**
Poor	0.14***	0.07***	0.01	0.02*	0.11***	0.03***	0.07***	0.07***
	(0.014)	(0.012)	(0.012)	(0.009)	(0.013)	(0.007)	(0.010)	(0.015)
Dep	0.30***	0.61***	0.59***		0.26***	0.58***	0.41***	0.40***
	(0.025)	(0.015)	(0.018)		(0.017)	(0.032)	(0.034)	(0.015)
Poor × Dep	0.05	0.05**	0.14***		−0.04	0.12**	0.05	0.15***
	(0.035)	(0.024)	(0.026)		(0.030)	(0.047)	(0.042)	(0.026)
Obs.	14824	14824	14824	3599	14824	14824	14824	14824
Entries	597	567	552	0	1175	230	511	1013
Exits	873	880	713	182	1496	200	553	1373

Note: Dependent variables are material deprivation (MD), low income (LI), low work intensity (LWI), low education (LE), poor housing (PH), overcrowded (OC), bad health (BH), health limitations (HL); cells show point estimates for coefficients of linear model with standard errors in parentheses; columns in panels are separately estimated; explanatory variables refer to poverty and deprivation status in $t-1$; indicated levels of significance are *** for $p < 0.01$, ** for $p < 0.05$ and * for $p < 0.1$, respectively.

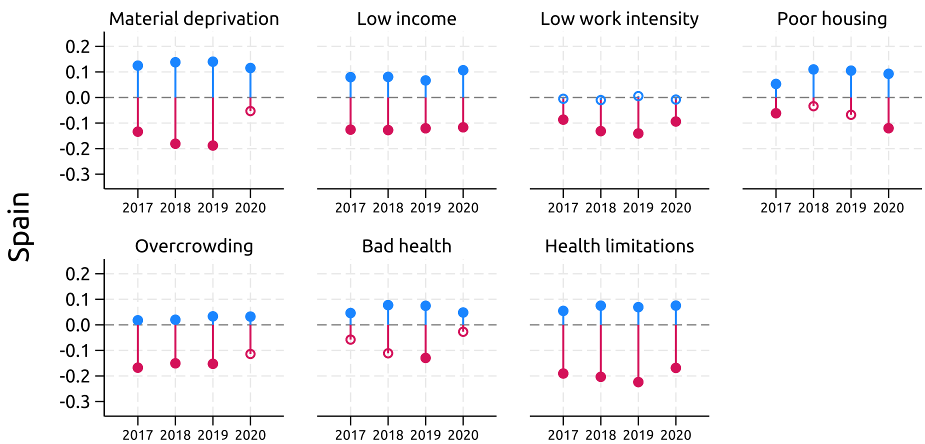

FIGURE 4 | Differences in deprivation entry and exit probabilities in Spain. Dots show differences in deprivation entry (●) and exit (●) probabilities between poor and nonpoor, hollow markers indicate insignificance ($p < 0.01$).

4.3 | Differences in Entry and Exit Probabilities

4.3.1 | Country-Specific Evidence

Instead of analysing individual model coefficients, one may also directly explore differences in deprivation entry and exit probabilities between poor and nonpoor for each indicator over time, as shown in Figure 4 for Spain. See Figure A2 for all other countries. Several observations are salient. For instance, Figure 4 reveals a certain stability over time for most indicators, although estimates may vary from year to some extent. Furthermore, in many instances a quantitatively different role of poverty for deprivation entries and exits is apparent. More specifically, past poverty status tends to decrease deprivation exit probabilities more than it increases deprivation entry probabilities, which corresponds to the previously observed positive coefficient for the interaction terms. Another way to interpret this finding is to view deprivations as more persistent for the poor than for the nonpoor people. In some cases, estimated differences are also insignificant (low work intensity) or missing (education). The latter follows from observing insufficient transitions (see also above).

A more in-depth rationalization of observed patterns may have to rely on country-specific trends or circumstances (e.g., the business cycle). For instance, most countries experienced a pronounced decline in the unemployment rate between 2013 and 2019. According to the Eurostat, Spain reduced its unemployment rate by some 12%-points (cf. Figure A4), which may result in fewer unemployment entries in general and explain the insignificant difference in low work intensity deprivation in particular. During this massive unemployment reduction in Spain, the poor were, however, less likely to leave deprivation in low work intensity.

4.3.2 | Cross-Country Evidence

To what extent are these patterns observed in other European countries as well? Figure 5 shows the differences in transition probabilities for deprivations between poor and nonpoor individuals in the previous year across different countries and years. Reddish dots show the difference in deprivation exit probabilities and are usually significantly negative ($p < 0.01$), indicating

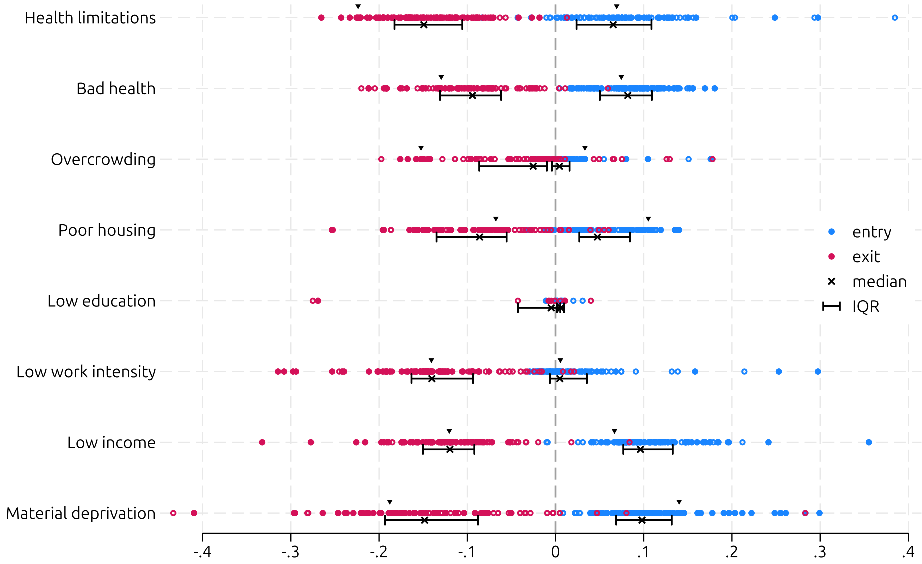

FIGURE 5 | Differences in deprivation transition probabilities across countries and years. Figure shows differences in deprivation entry (●) and exit (●) probabilities between poor and nonpoor, hollow markers indicate insignificance ($p < 0.01$); ▼ indicates vales for Spain in 2019; pooled estimates for all countries and 4 year-to-year changes.

that individuals poor and j-deprived in $t-1$ are less likely to leave deprivation j than nonpoor and j-deprived individuals (insignificant estimates are represented by hollow markers). Bluish dots, in turn, show the difference in deprivation entry probabilities and are usually significantly positive ($p < 0.01$), indicating that individuals who were poor and not j-deprived in $t-1$ are more likely to enter deprivation j than individuals nonpoor and non-j-deprived in $t-1$.

Moreover, Figure 5 also shows median entry and exit probabilities for each indicator (depicted as black X). The median entry probability difference for material deprivation is, for instance, about 0.1, meaning that typically poor in $t-1$ are 10%-points more likely to enter this deprivation than nonpoor (conditionally on being nondeprived in $t-1$). Instead, the median exit probability difference for material deprivation suggests that the poor are usually 15%-points less likely to leave this deprivation. More generally, it is not uncommon to observe differences in exit probabilities between −0.3 and −0.1 across indicators and differences in entry probabilities between 0.05 and 0.1. Indeed, by tendency, differences in exit probability are larger than in entry probability, suggesting poverty to play a particularly important role in impeding to leave deprivations, although results depend on indicator an country. Similar results also emerge for plausible alternative choices of the poverty cutoff, see Figure A3 in Appendix A.

Finally, Figure 5 also illustrates two exceptions. First, some indicator-country-year combinations result in insignificant differences (e.g., for education), which largely follow from insufficient observations (cf. entry and exit observations in Table 2). Second, and perhaps more interestingly, for some indicator-country-year combinations of the difference estimate turns out to be significant with an unexpected sign (e.g., for entry probabilities into low-work-intensity deprivation). As several phenomena may produce such a finding, identifying the exact mechanism requires further in-depth analysis. A pronounced economic downturn may, for instance, force otherwise not-deprived individuals to substantially reduce working hours. Section 5 will return to this issue.

4.4 | Effect Heterogeneity in Poverty Profiles

Poverty has many faces and multidimensional poverty may originate from very different combinations of deprivations. While Suppa et al. (2022) propose an in-depth analysis of deprivation profiles and bundles, for the present context deprivation-specific censored headcount ratios together with the incidence of poverty already provide important insights and are shown in Figure 6 for Spain in 2019. Specifically, censored deprivation rates vary between 2% and 10% which implies, together with an incidence of 15%, that each deprivation indicator usually afflicts less than half of the poor. Put differently, there is no deprivation indicator which all of the poor suffer from. Moreover, Figure 6 also shows that censored headcount ratios are in part considerably smaller than their uncensored counterparts, which implies that there is no deprivation which immediately entails poverty either. This evidence suggests that poverty (understood as multiple deprivation) does manifest itself in many different shapes and forms.

The approach proposed in this article relies on the poverty status to offer a summarising assessment of whether deprivations further coupled or perhaps even decoupled over the previous year. Occasionally, one may however also wish to unfold the embodied effect heterogeneity to some extent. For instance, one may wonder whether the observed patterns actually only originate from deprivation in a single indicator which happens to be widespread among many of the poor, such as low education (which afflicts about two-thirds of the poor according to Figure 6). Similarly, one may ask whether experiencing a particular deprivation results in systematically higher or lower probabilities of entering or leaving another specific deprivation. Given that different mechanisms (cf. Section 3.1 related to different indicators are to be expected, the question is to which extent the focus on the poverty status

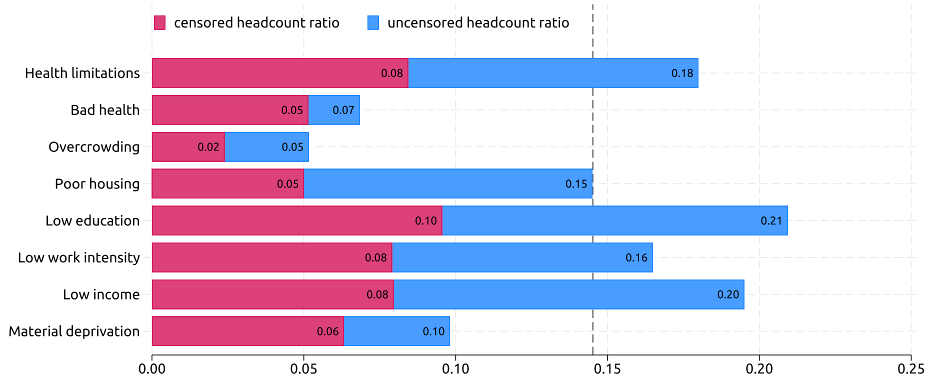

FIGURE 6 | Censored and uncensored headcount ratios in Spain 2019. The dashed line is the headcount ratio.

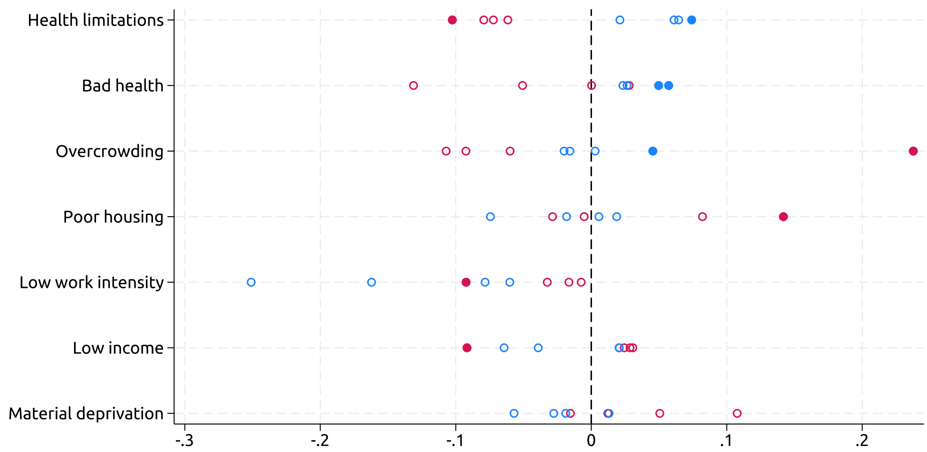

FIGURE 7 | Difference in transition probabilities for educational deprivation conditional on being poor in Spain. Dots show differences in deprivation entry (●) and exit (●) probabilities between people who are deprived in education and those who are not, conditional on being poor; hollow markers indicate insignificance.

may obscure instructive effect heterogeneity). More specifically, one may thus ask whether conditional on being already poor in $t-1$, the probability to enter a further deprivation j differs with the presence of a deprivation in some indicator j'. Formally, one would seek to reject the hypothesis that

$$\Pr(d_{ijt} = 1 | \text{poor}_{it-1} = 1 \wedge d_{ijt-1} = 0 \wedge d_{ij't-1} = 0)$$
$$= \Pr(d_{ijt} = 1 | \text{poor}_{it-1} = 1 \wedge d_{ijt-1} = 0 \wedge d_{ij't-1} = 1) \quad \forall j \neq j' \tag{H.5}$$

and

$$\Pr(d_{ijt} = 0 | \text{poor}_{it-1} = 1 \wedge d_{ijt-1} = 1 \wedge d_{ij't-1} = 0)$$
$$= \Pr(d_{ijt} = 0 | \text{poor}_{it-1} = 1 \wedge d_{ijt-1} = 1 \wedge d_{ij't-1} = 1) \quad \forall j \neq j' \tag{H.6}$$

To test these hypotheses one may modify model (5) to include interaction terms for each occurrence of poor_{it-1} with the deprivation in an indicator j' and thus estimate

$$\Pr(d_{ijt}) = \alpha + \beta \text{poor}_{it-1} + \beta^{j'} \text{poor}_{it-1} \times d_{ij't-1} + \gamma d_{ijt-1} + \delta \text{poor}_{ijt-1} \times d_{ijt-1} + \delta^{j'} \text{poor}_{ijt-1} \times d_{ijt-1} \times d_{ij't-1} + \epsilon_{it} \quad \forall j \neq j' \tag{10}$$

Testing for systematically different transition probabilities related to the presence of a deprivation j' amounts to testing the null hypotheses $\widehat{\beta^{j'}} = 0$ and $\widehat{\beta^{j'}} + \widehat{\delta^{j'}} = 0$, respectively.[11]

Figure 7 illustrates such an analysis by exploring whether the role of poverty for deprivation entries and exits differs systematically if poverty involves deprivation of education. More specifically, Figure 7 shows estimated differences between persons who are education-deprived and those who are not conditional on being poor using several years of Spanish data. Broadly speaking, results suggest that in most cases there is no significant difference. While significant differences can be observed in some years for some indicators, the sign of the difference cannot be immediately rationalised. The reason is that nondeprivation in education in this analysis does not imply that those individuals necessarily experience a lower deprivation score, since after all the analysis conditions on being poor. In summary, I do not find evidence that results systematically differ for the poor who experience deprivation in education compared with the poor who do not. The lack of statistical power may however caution against too strong conclusions.

Such analyses of effect heterogeneity thus likely suffer from similar limitations as the analysis of individual indicators, namely that cell sizes may prove critically small and the few observed deprivation entries among the poor have to be further divided according to their specific deprivations (as already suggested in the discussion of Table 2). On the one hand, this challenge may be seen as one of insufficient data and not as a limitation of the principle approach. On the other hand, one may expect to frequently encounter this issue in practice, as deprivation indicators usually refer to relatively small proportions of the population. The focus on the (past) poverty status, as explored in this article may, therefore, provide a promising alternative to overcome this issue, while offering a meaningful and coherent interpretation in terms of more general patterns within the overall measurement framework.

5 | Discussion

5.1 | Interpretative Scope and Limits

All in all, did deprivations over the previous year further couple, remain the same or perhaps even decouple? To answer this question I suggest analysing annually computed differences in deprivation entry and exit probabilities between poor and nonpoor. I provide four remarks on what this information may reflect and which conclusions are supported.

First, the adopted approach does not feature any identification strategy to isolate correlation which would permit a causal interpretation. While the timing structure of the dynamic model does purge the contemporaneous correlation of multidimensional poverty and its deprivations (it ignores both other deprivations and poverty in t), important sources of endogeneity remain. More specifically, poverty and deprivation status in $t-1$ may be mechanically related, simultaneously determined or both. In particular, observed or unobserved heterogeneity (e.g., personality traits, ability or effort) may be correlated with the poverty status. While it may seem acceptable for a summary measure to reflect the influence of these factors, some of those may be beyond the reach of policymakers and thus unnecessarily compromise policy relevance. Recalling that the proposed analysis seeks to summarize patterns of deprivation transitions in multidimensional poverty, either way can be justified.

Accordingly, once long-run panel data are considered, the presented analysis may be extended in several ways. Besides controlling for time-constant unobserved heterogeneity (e.g., personality traits), pooling many years would also permit an in-depth analysis of sociodemographic factors. While it is technically straightforward to introduce policy-relevant sociodemographic covariates (e.g., age, sex, region) into the analysis, small cell sizes may undermine a more rigorous analysis. For instance, Table A3 in Appendix A shows that females have a higher probability to experience deprivation in low work intensity in period t in numerous countries. However, more data is needed to examine whether women are more likely to enter low work intensity, less likely to leave it, or both.

Second, as discussed in Section 3.1 each pair of indicators may be related by one or more mechanisms and some deprivations may, moreover, function as moderators (e.g., low education). Additionally, an in-depth analysis of deprivation interlinkages suggests that multidimensional poverty usually comprises different deprivation profiles (Suppa et al. 2022). As a consequence, several mechanisms which are related to different indicators may all be jointly operative and result in the observed differences in transition probabilities. The approach to rely on the poverty status as the main distinction for the proposed analysis (which requires multiple deprivation in the first place) seeks to provide a useful summary of those dynamics.

Third, the presented evidence suggests in general rather stable patterns over time for most indicators, although there is year-to-year variation, too. Moreover, occasionally transition probability differences are insignificant or may even have an unexpected sign in some years (e.g., low work intensity). How may such patterns be rationalised? Recall that poor people might be more likely to enter an additional deprivation for very different reasons, which include mechanisms related to their already experienced deprivations (as discussed above). On the one hand, many of these mechanisms are in some sense more structural and relate, for instance, to the functioning of the healthcare system (e.g., in terms of required resources and entitlements), the functioning of insurance markets or hiring protocols and practices of employers. On the other hand, differences in transition probabilities may also change with macroeconomic developments (e.g., the business cycle as discussed above) or specific policy measures. Consider, for instance, a perfectly targeted policy measure which only helps to overcome low work intensity for the poor. If large enough, such a policy may render the poor even *more* likely to leave the deprivation than the nonpoor. The interplay of structurally related processes, relevant macro-economic trends and various policies may then produce patterns such as the observed.

Based on the previous considerations differences in the transition probabilities may be understood as a "net effect" of the various factors operative in a particular year and thus be interpreted as follows. Observing $\Delta^{\text{entry}} > 0$ and $\Delta^{\text{exit}} < 0$ each suggest deprivations to couple and transitions probabilities to be at the disadvantage of the poor, so *anti-poor*. If instead, $\Delta^{\text{entry}} = 0$ and $\Delta^{\text{exit}} = 0$ transitions or trends may be considered as *neutral*. Finally, $\Delta^{\text{entry}} < 0$ or $\Delta^{\text{exit}} > 0$ would mean that trends have been *pro-poor* and deprivations decoupled during the period of observation. In this sense, both statistics may be used for monitoring purposes on an annual basis (while making use of the information of the panel component).

Finally, overcoming every deprivation is important by-itself. A well-constructed multidimensional poverty measure relies on deprivation indicators, which already reflect normatively undesirable shortfalls. The presented evidence, however, additionally suggests that nondeprivation in one indicator may help to prevent further deprivation in other indicators. Put differently, nondeprivation in one dimension is also instrumentally relevant for improving human well-being in another dimension; see Sen (1999) for a discussion of intrinsic and instrumental relevance of dimensions of human well-being. The presented evidence, therefore, also resonates well with research on monetary poverty dynamics, which concludes that preventing people from falling into poverty in the first place may be an effective measure due to substantial state-dependence (Biewen 2014). Long-run panel data would permit an in-depth analysis of nondeprivation as well.

5.2 | Deprivation Indicators Reflecting Stocks

The presented analyses also reflect a previously recognized shortcoming of so-called stock indicators, which feature an inherent inertia by construction. In particular, deprivation indicators drawing on years of education, the highest educational degree obtained, disability status or experienced child mortality in the household, can barely change over time (e.g., Dotter and Klasen 2014; UNDP and OPHI 2019). For instance, re-entering education deprivation after completing the required level is essentially impossible. Besides exhibiting little variation, the real concern regarding such indicators is their weak policy relevance, as they are usually insufficiently sensitive to related policy measures (e.g., literacy programs). Responsiveness to effective policy interventions is, however, an important requirement for social indicators more generally (Atkinson 2002, 22). For monitoring purposes, repeated cross-sectional sampling may mitigate this issue to some extent, as improvements in the aggregated indicator are at least possible, even though levels may only slowly decline.

For a transition-oriented panel data analysis at the micro-level, however, stock deprivation indicators essentially escape a meaningful analysis. Specifically, as often deprivation entries or exits (or both) are not observed at all, it may be impossible to estimate some of the parameters (see Tables 2 and A1). Consequently, differences in deprivation entry or exit probabilities cannot be computed either (see, e.g., Figure 5).[12] Nonetheless, stock indicators such as education in the present case, may play a meaningful role in dynamic analysis, as illustrated in Section 4.4, as their presence may be presumed to entail systematic interlinkages with other deprivations. As a consequence, the outlined analytical limitations of stock indicators may be considered during the initial construction of the multidimensional poverty index, together with other needs of the measure.

6 | Concluding Remarks

To illuminate the dynamics of multidimensional poverty at the micro level, this article proposes a framework to analyse the interplay of its deprivation indicators, that is, measure-inherent dynamics. Specifically, I suggest analysing differences in deprivation entry and exit probabilities between (multidimensionally) poor and nonpoor individuals. Annually computed differences in these transition probabilities emerge as a useful summary measure to assess whether, all in all, deprivations further couple, evolve neutrally or perhaps even decouple over the previous year. The presented approach may be applied using short-run panel data. An illustration with EU-SILC data suggests, broadly speaking, rather stable patterns over time for most indicators and largely supports the idea that initial deprivations beget further deprivations. An important implication of the presented evidence is that coordinated programmes and measures across policy fields are critical for both overcoming already-experienced deprivations and preventing entry into new deprivations. An empirical finding of this article is that there is interesting year-to-year and cross-country variation in the difference of deprivation transition probabilities. Consequently, one line of future research may explore these patterns in greater depth. For instance, one could assess the impact of shocks or social arrangements with respect to their role in encouraging, reducing or preventing the accumulation of deprivations.

The proposed analysis has also limitations. First, while the evidence may be rationalised with recourse to several mechanisms or sources, other factors such as unobserved heterogeneity (e.g., personality traits, effort or ability) cannot be ruled out. Second, the presented analysis may not sufficiently address sample attrition, which may be an issue in some countries more than in others. Since usually poor and deprived respondents are more likely to leave the survey, deprivation exits and entries of the poor are presumably over- and underestimated, respectively. Consequently, differences in transition probabilities may draw an overly optimistic picture and thus be rather seen as lower bound estimates. To address these shortcomings, a second line of future research may refine the presented analyses for situations where longer-running panel data is available (e.g., for a single country). Major advantages of having repeated observations at the micro level, include that data rounds can be pooled and, as cell sizes increase, e.g., socio-demographic variables can be thoroughly integrated into the analysis, beyond serving as a control variable. One may explore, for instance, potential gender or regional disparities in entering or leaving certain deprivations. Similarly, controlling for unobserved heterogeneity (e.g., personality traits) becomes easier as well, although panel attrition may play a more prominent role. Moreover, as longer (non-) deprivation spells become observable, the role of persistent (non-) deprivation may be studied in greater detail, too.

Finally, the proposed analysis seeks to better understand multidimensional poverty dynamics and illuminate how the joint distributions of deprivations are changing over time. The principle approach may, however, also be used in settings not directly concerned with multidimensional poverty, since technically the underlying MPI is not required. One may, for instance, study whether individuals with a low working intensity are less likely to leave and more likely to enter income poverty. Indeed, the basic approach might even be adapted to socio-demographic variables. For instance, one could study whether young or old persons are more likely to enter or leave income poverty. Such applications seem worth exploring as the current use of the longitudinal component of the EU-SILC for informing policy has been questioned (Jenkins and van Kerm 2014) and indicators on transitions may be included in the social inclusion portfolio (Social Protection Committee 2022, 84).

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Ethics Statement

The author has nothing to report.

Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

The underlying household data are distributed by Eurostat. Researchers may apply for access to the scientific use files.

Endnotes

[1] See https://mppn.org/applications/national-measures/ for related applications.

[2] Specifically, the at risk of poverty and social exclusion rate (AROPE) relies on (i) a severe material and social deprivation index, (ii) a low-work intensity indicator and (iii) a relative income poverty component.

[3] Indeed, for similar reasons first-order Markov models became the workhorse for research on monetary poverty dynamics (e.g., Cappellari and Jenkins 2004; Ayllón 2014; Mussida and Sciulli 2022).

[4] Individual-level measures have been adopted in other country contexts as well (e.g., Vijaya et al. 2014; Mitra and Brucker 2019; Burchi et al. 2022).

[5] It is a well-known issue for household-level measures that some households may lack eligible members (e.g., children) to experience a particular deprivation (e.g., in school attendance); see, Dotter and Klasen (2014); Alkire et al. (2015); UNDP and OPHI (2019).

[6] Specifically, I use EU-SILC release 1 in 2022 (DOI: 10.2907/EUSILC2004-2020V.2).

[7] For instance, some survey questions underlying the revised material and social deprivation index have been distributed with the panel component of the data for the first time in 2017. Adding previous years would, therefore, require to adopt a less comprehensive and relevant indicator (or to accept spurious transitions confounding the presented analyses).

[8] As the EU-SILC is based on ex-ante output harmonization national statistical offices, who share the survey data with Eurostat, may opt for slightly different survey designs and different nonresponse adjustments, for instance.

[9] In particular, the LPM may produce implausible individual predicted probabilities outside the 0–1 interval, which are, however, irrelevant for the proposed analysis as it focuses on differences in average predicted probabilities instead. Going beyond Table A2, a more systematic comparison of the average predicted probabilities, moreover, suggests that estimates begin to differ in the 6th (4th) decimal digit for the point estimate (standard error), which affects 11 (6) country-year-indicator combinations, respectively. Overall, the analysis covers the estimation of some 2500 average predicted probabilities.

[10] Evidence for all countries and years suggests similar conclusions (see Figure A1). The particular role of the past poverty status for deprivation entries and exits seems to vary in magnitude by country and indicator. In general, however, the evidence suggests that the poverty status has rarely the same quantitative role for deprivation entries and exits, which is in line with H.3.

[11] Indeed, other approaches to examine effect heterogeneity may be explored too. Instead of relying on a single deprivation to partition the set of the poor in two groups, one could easily rely on two or more deprivations (e.g., complete deprivation in an entire dimensions such as health or housing in the present case). Alternatively, one may also argue for an interaction of the deprivation status of j in $t-1$ with the deprivation status of j' in $t-1$. Another option would be to create different classes based on deprivation profiles as discussed in Suppa et al. (2022). Finally, one could discard the poverty status altogether and exclusively study deprivation indicators with potentially numerous interactions instead. Either way, further analyses along these lines would also require thorough theoretical guidance. Both are left for future research.

[12] This high degree of inertia also manifests in education deprivation having by far the lowest deprivation entry and exit rates (cf. Figure 3) and extremely high average predicted deprivation probabilities of around 95% given education deprivation in $t-1$, which are largely independent of the poverty status (see Table A2).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Appendix.**